

Research Foundation

Bilge Erten* and Oliver Schwank

Rethinking Unconditional Convergence in Manufacturing in the Age of New Technologies

<https://doi.org/10.1515/jgd-2020-0011>

Received April 20, 2020; accepted March 9, 2021

Abstract: We revisit unconditional convergence within manufacturing with a focus on differences in technology intensity across industries. For Latin American and Sub-Saharan African economies, we observe that low-technology and medium-technology intensive industries experience a significantly slower convergence in comparison to high-technology intensive ones. In contrast, we find no evidence of a significant differential for low-technology industries' convergence in Asian economies, and if anything, we see that medium-technology intensive sectors experience a faster convergence than high-technology industries. In developed economies, we observe that while low-technology industries experience a slightly slower convergence, medium-technology industries converge at similar rates to high-technology industries. We also find that these differences emerge during the period of increased global integration, which exposed developing economies to increased competition both from advanced markets and fast industrializers within the developing world. Finally, we show that differential convergence patterns are stronger after the peak of manufacturing employment share has been reached. We discuss the implications of these trends for the future of development policy making.

Keywords: technology intensity, globalization, convergence, productivity

1 Introduction

Despite the absence of economy-wide convergence across countries, it has been well-documented that formal manufacturing industries exhibit unconditional

*Corresponding author: **Bilge Erten**, Department of Economics, Northeastern University, 43 Leon Street, 312A Lake Hall, Boston, MA 02115, USA, E-mail: b.erten@northeastern.edu

Oliver Schwank, Senior Economist, Department of Economic and Social Affairs, United Nations, New York, NY, USA, E-mail: schwank@un.org

convergence in labor productivity (Madsen and Timol 2011; Rodrik 2012). This implies that industries that have initially lower levels of labor productivity experience more rapid growth in labor productivity, allowing them to catch up with industries at the technology frontier. The evidence shows that this process is unconditional within manufacturing industries; that is, it does not depend on specific characteristics, policies, or institutions of countries. Given the positive externalities of manufacturing to other sectors and economy as a whole, one potential implication of this finding is that developing countries should aim to kick start manufacturing production even if it will be rather inefficient at the initial stages. Due to unconditional convergence, such manufacturing industries are likely to absorb new technologies through global production networks, and achieve higher labor productivity over time. In fact, this viewpoint has been the main motivation for industrial policies widely implemented across developing countries.¹

Yet, it has also been documented that many developing countries have been experiencing premature deindustrialization, particularly driven by declining shares of manufacturing employment in total employment (Felipe, Mehta, and Rhee 2019; Haraguchi, Cheng, and Eveline Smeets 2017; Rodri 2016; Tregenna 2009, 2011). The evidence suggests that skill-biased technological change and globalization explain the degree to which countries prematurely deindustrialize, without obtaining the full benefits that come from the industrialization process.

In this paper, we revisit unconditional convergence within manufacturing with a focus on differences in technology intensity across industries. The technology intensity of manufacturing industries matters for productivity growth for a number of reasons: (1) most countries start industrializing at the lower end of the technological spectrum, producing low-technology intensive manufactures, such as textiles, food, and raw materials. If convergence effects are lower for these industries, this will have implications for how fast a lagging industry may achieve frontier productivity rates and how fast such effects may spillover to other sectors. (2) New and emerging (partly digital) technologies that foster automation and computerization have been pushing the technological frontier further out across several industries, but particularly strongly for low- and medium-technology intensive sectors, including textiles, automobiles, and other industries with a high volume of routine tasks (Frey and Osborne 2017). If the technology frontier is shifting outward faster in these categories, these technological advancements may also make it more difficult to converge. (3) The intensity of global competition also varies by technology intensity across industries. Since low-technology intensive products are easier to replicate and reverse engineer, there is a higher likelihood of

¹ See, for example, Harrison and Rodríguez-Clare (2010) for a survey of the literature on industrial policy and arguments developed for and against it.

new entrants from low-cost countries where wages are low, and a greater risk of being out-competed by producers from countries that have a comparative advantage in producing low-technology manufactures.

More specifically, we examine whether there are significant differences in convergence rates by technology intensity of manufacturing industries. Using the technology intensity definition proposed by the OECD, we categorize industries into three groups based on their R&D intensities (i.e. direct R&D expenditures as a percentage of gross output): low-, medium-, and high-technology intensive industries (Galindo-Rueda and Verger 2016). We then test whether low-technology intensive industries exhibit convergence rates that differ from medium- and high-technology intensive industries, and whether such differential convergence rates are more significant for certain groups of developing countries.

To this end, we employ data from the United Nations Industrial Development Organization's (UNIDO) industrial statistics database, which relies on country-specific industrial surveys (UNIDO 2017). Since these surveys generally exclude small, informal firms, the results documented in this paper should be regarded as applying to more formal firms within manufacturing sectors. We also use country-level manufacturing employment and output data to show recent trends in premature deindustrialization that is increasingly observed in recent decades.

Our primary findings indicate that there are important differences across country groups in unconditional convergence by technology intensity. For Latin American and Sub-Saharan African economies, we find that low-technology and medium-technology intensive industries experience a significantly slower convergence in comparison to high-technology intensive ones. In contrast, we find no evidence of a significant differential for low-technology industries' convergence in Asian economies—instead, we find that medium-technology intensive sectors experience a faster convergence than high-technology industries in these countries. In developed economies, we observe that while low-technology industries experience a slightly slower convergence, medium-technology industries converge at similar rates to high-technology industries.

We further examine whether the rate of unconditional convergence across industries varies across time. In particular, we test whether the differential convergence patterns we observe emerge during the period of global integration, which generally exposed developing economies to increased competition both from advanced markets and also from fast industrializers within the developing world. We find that for the most part, the differential convergence patterns emerge in post-1985 period, and we find no evidence of a significant difference across industries before the onset of global integration.

A related and equally noteworthy explanation for why we observe differential convergence across industries in certain regions could be that these economies

might have experienced premature deindustrialization (Felipe, Mehta, and Rhee 2019; Haraguchi, Cheng, and Eveline Smeets 2017; Rodrik 2016; Tregenna 2009, 2011). The latter is particularly important in the presence of automation-related technology shocks that render it more difficult to reach the technological frontier as well as increased competitive pressure in the global markets from newly emerging competitors. To examine this channel, we test whether differential convergence emerges after the peak of manufacturing employment share has been reached. Our findings show that low- and medium-technology industries begin to converge at slower rates in Latin America and Sub-Saharan Africa after the employment deindustrialization begins to take place. This is also the case for low-technology intensive industries in developed economies. In contrast, we find no evidence that differential convergence takes place before the peak of manufacturing employment is reached.

Finally, we examine whether the differential convergence patterns across countries can be explained by their comparative advantage. In particular, we would expect that countries specialized in producing manufactured goods due to their comparative advantage to perform better in terms of unconditional convergence in manufacturing. We find evidence that differential convergence, particularly for low-technology intensive manufactures, is significant for the non-manufactures exporters. In contrast, for manufactures exporters, the low- and medium-tech industries experience at least as high convergence rates as the high-tech industries. These results are consistent with the view that specialization patterns driven by comparative advantage matter for explaining patterns of differential convergence by technology intensity.

1.1 Related Literature

Our work contributes to the growing literature on understanding the dynamics of (un)conditional convergence across countries and industries. Early studies in the 1990s focused on testing convergence with the goal of differentiating between endogenous growth models and neoclassical growth theories (see, for example, Mankiw, Romer, and Weil (1992)). It is a well-established fact that when we take developing countries as a whole, there is no systematic tendency for them to grow faster than rich countries over time. The convergence effects only appear when we condition on country-specific characteristics such as institutions, policies, and other circumstances. There is evidence of unconditional convergence only within the group of Organisation for Economic Co-operation and Development (OECD) countries (Baumol 1986; De Long 1988), and among regions within a unified economy such as the U.S. (Barro et al. 1991). More recently, however, studies have shown evidence of unconditional convergence for manufacturing within OECD

(Madsen and Timol 2011) and for manufacturing industries covering both developed and developing countries (Rodrik 2012). Similarly, there is also recent evidence showing unconditional convergence for service industries (KinfeMichael and Morshed 2019). We contribute to this literature by demonstrating the presence of systematic differences in unconditional convergence by technology intensity of manufacturing industries.

A related body of literature examines the determinants of premature deindustrialization in manufacturing. A large body of work going back to Kaldor (1966) focused on causes of early deindustrialization in the British context (see, for example, Singh 1977; Rowthorn and Wells 1987). The term ‘premature deindustrialization’ was first used by Dasgupta and Singh (2006) to refer to the fact that developing countries began to deindustrialize at levels of income that are a small proportion of those at which developed countries started to turn into service economies. Palma (2008) and Tregenna (2009) focused on developing a better conceptualization of deindustrialization by focusing not only on manufacturing employment, but also manufacturing output shares for a much broader set of countries. Building on this work, recent studies analyzed the factors that explain premature deindustrialization, with a focus on technology and trade shocks (Felipe, Mehta, and Rhee 2019; Haraguchi, Cheng, and Eveline Smeets 2017; Harrison 2019; Rodrik 2016). Our study contributes to this growing literature by showing how these shocks also matter for explaining differential convergence by technology intensity across manufacturing sectors.

Finally, our study relates to the extended literature on the effects of new technologies as well as technological capabilities on economic development. Early studies focused on understanding the role of industrial policy in developing technological capabilities at the firm and national levels, and the importance of this process for achieving economic development (Amsden and Hikino 1993; Lall 1992). With the rise of digitization and automation as new technologies, several studies have aimed to understand whether these new technologies are conducive to economic development in poor countries (De Souza 2017; International Monetary Fund 2019; Rodrik 2018; United Nations 2018; World Bank 2019). It is generally recognized that these technologies present new opportunities for developing countries; however, they may also create new challenges. In this paper, we focus on some of the challenges new technologies may pose on developing countries based on their existing patterns of industrial specialization, but these also present opportunities for countries that invest in technological upgrading to move up in the industrial ladder.

The remainder of the paper proceeds as follows. Section 2 provides a conceptual framework, and Section 3 describes the data sources used in our analysis. Section 4 presents the empirical strategy and results. Section 5 concludes and draws policy implications.

2 Conceptual Framework

We briefly discuss the recent trends in deindustrialization, and how the main drivers of deindustrialization—primarily skill-biased technological change and globalization—may explain differential convergence rates in labor productivity across manufacturing industries. This discussion guides the empirical framework and analysis in Section 4.

It is well-known that manufacturing exhibits an inverted U-shaped pattern over the course of development. That is, the share of population employed in manufacturing increases as countries begin to industrialize, followed by a subsequent decline as the economy shifts away from manufacturing into the provision of services. Yet, the turning point in which economies begin to deindustrialize started to occur at much lower levels of income in the recent time period. This process of premature deindustrialization is particularly concerning for developing countries in which manufacturing industries began to shrink without reaching maturity and at levels of income that were much lower than those at which developed countries began to deindustrialize.

Figure 1 illustrates the simulated relationship between manufacturing share of employment and income per capita. Following earlier studies (Felipe, Mehta, and Rhee 2019; Rodrik 2016), we use a quadratic estimation with country and period fixed effects, controlling for population size. We divide the time period into three parts: (i) pre-1980, (ii) 1980–2000, and (iii) post-2000. Consistent with the premature deindustrialization view, we observe that the inverse U-shaped relationship has been shifting downwards over time, with the post-2000 period showing that the peak is reached at much lower levels of income than the earlier episodes of development. In addition, we also see that the turning point decreases at each episode, implying that the maximum attainable employment share for manufacturing is reduced in each episode. An implication of this observation is that the ability of manufacturing to absorb large quantities of low-skilled work force is increasingly reduced over time.

Figure 2 shows the simulated relationship between manufacturing share of output (measured by the manufacturing value added divided by GDP at constant prices) and income per capita. Although we continue to observe a downward movement in this relationship, this is much smaller compared to the one we observe for manufacturing employment share as illustrated in Figure 1. The main reason for this difference is that while productivity improvements in manufacturing lead to a decline in employment in this sector, in turn they result in an improvement in output since better technology allows fewer workers to produce a greater level of output. Hence, although as a share of total GDP manufacturing value added also starts to decline over

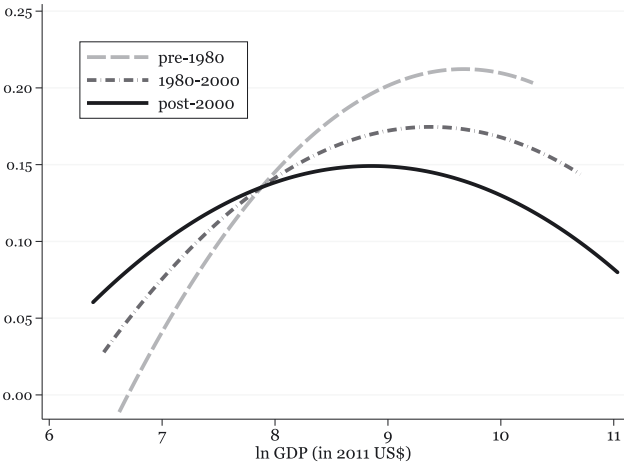


Figure 1: Simulated manufacturing employment shares. *Note:* The figure displays simulated manufacturing employment shares as a function of income (in GDP per capita in 2011 international dollars) using a quadratic estimation with country and period fixed effects, controlling for population size. For further details on data and methodology, please see text.

time as economies become more service-oriented, this is a much slower process, allowing for post-industrial economies to continue their production of industrial goods at relatively large volumes.

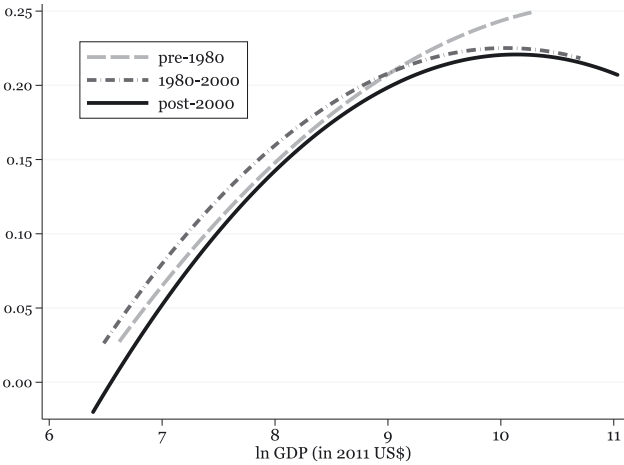


Figure 2: Simulated manufacturing output shares. *Note:* The figure displays simulated manufacturing output shares (measured by the manufacturing value added divided by GDP at constant prices) as a function of income (in GDP per capita in 2011 international dollars) using a quadratic estimation with country and period fixed effects, controlling for population size. For further details on data and methodology, please see text.

Among the drivers of premature deindustrialization, previous research has emphasized two main factors (Lawrence and Edwards 2013; Rodrik 2016). First, during the process of structural transformation, manufacturing industries experience faster productivity growth compared to other sectors. This results in a shift of workers previously employed in manufacturing into other industries, in particular towards services. As a result, we observe that the employment share of manufacturing peaks and begins to decline as structural change occurs over time. Second, if this decline in employment share of manufacturing is accompanied by a decline in its output share as well, this generally results from increased global competition that manifests itself in a negative trade balance in manufactures or a shifting demand away from manufactures (Rodrik 2016). In other words, exposure to increased global competition due to trade shocks results in some firms in less-productive countries to exit the market, resulting in a lower output share of manufacturing coupled with a lower employment share.

Meanwhile, the presence of unconditional convergence in labor productivity within manufacturing industries may generate the impression that manufacturing still has a special role in fostering structural change and economic catch-up in low-income countries, no matter what the initial conditions of these economies are. However, the benefits of unconditional convergence in manufacturing productivity depend on the technology intensity of manufacturing industries that countries specialize in, primarily because of the effects of the same factors driving premature deindustrialization. First consider skill-biased technological change. There is now a growing body of evidence showing that new technologies linked to artificial intelligence and more broadly automation capabilities have been raising the technological frontier in producing several relatively labor-intensive industries that cluster in low- and medium-technology intensive sectors (Frey and Osborne 2017). These include food manufacturing, textiles, toys, automobiles, as well as several other manufacturing industries with a high share of routine tasks that are easily automatable. The faster shift of the technological frontier in these sectors make it more difficult to emulate these new production processes by the lagging producers, and hence, more difficult to converge to the same productivity levels.

Second, as another driver of premature deindustrialization, the degree of global competition also varies by technology intensity of manufacturing industries. Given the easy replicability of low-technology intensive products, these sectors observe a larger volume of new producers from low-wage developing countries. This results in a higher degree of competition in international markets for low- and medium-technology products compared to high-technology ones that are much more difficult to replicate and reverse engineer. In addition, the sunk costs to undertake relatively lower technology intensive production are also less than those required to produce higher technology intensive goods. If the existing producers of low-technology goods fail to

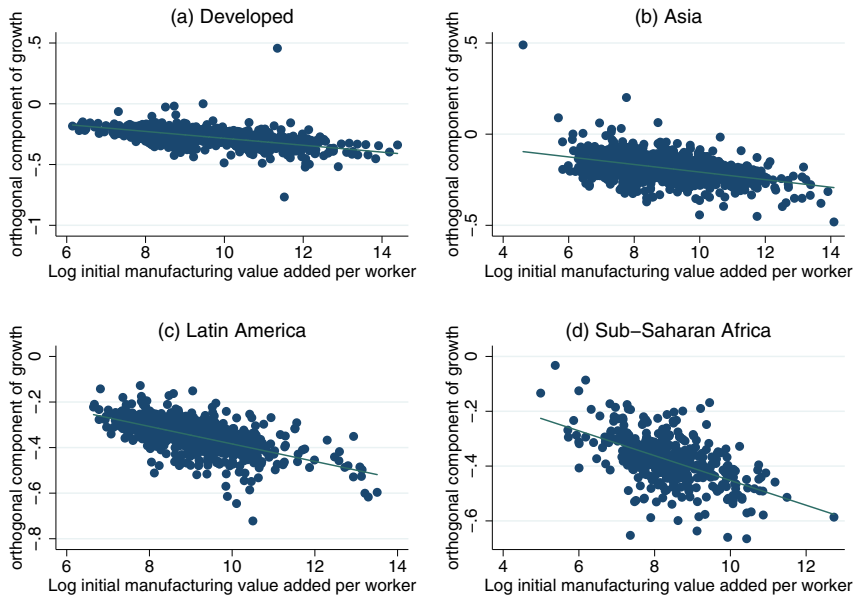


Figure 3: Unconditional convergence in two-digit manufacturing sectors by region. *Note:* The variable on the y-axis is the growth of value added per worker in two-digit manufacturing industries across four country groups (i.e. developed countries, Asian countries, Latin American countries, and Sub-Saharan African countries), controlling for industry, period, and period $\times$ industry fixed effects, where for each country we include five decades 1965–1975, 1975–1985, 1985–1995, 1995–2005, and 2005–2015. The data comes from INDSTAT2. For further details on data and methodology, please see text.

technologically upgrade, they can easily run into the risk of being outcompeted by new entrants from low-cost countries. To the extent that such capabilities for technological upgrading vary by country groups, we may observe differences across countries in how they are affected by these differential competitive pressures generated by exposure to trade shocks.

Potentially, both of these factors—skill-biased technological change and globalization—have constraining effects on the ability to realize unconditional convergence in industries with low- and medium-technology intensity. Given that most poor economies begin to industrialize at the lower end of the technological spectrum, the potentially lower convergence effects in these sectors will have implications for how fast an economy can undergo structural transformation.

Prior to testing for differential convergence, it is also useful to illustrate unconditional convergence within manufacturing industries. Figure 3 shows that, regardless of the regional classification, manufacturing industries that begin at lower levels of labor productivity experience faster growth in labor productivity. Since we do

not control for country fixed effects, this figure demonstrates that manufacturing has a strong tendency to exhibit unconditional convergence. In Panel (a), we observe unconditional convergence for developed economies, compared to Panels (b), (c), and (d) that display the same tendency in productivity convergence in different regions of the developing world, focusing on Asia, Latin America, and Sub-Saharan Africa. The steeper slope of the lines in the latter panels indicate that the baseline convergence estimates are larger in developing countries, which is not surprising since we expect the initially lagging industries to exist in higher proportion in these countries.²

In the following sections, we will examine whether there is any evidence for differential convergence by technology intensity, and whether this process differs by country groups as well as over time.

3 Data

The empirical analysis incorporates two primary sources of data: industry-level data on formal manufacturing employment and value added, country-level data on total manufacturing employment and value added as well as other time-varying, country-specific variables. We will discuss each data source in turn.

3.1 Industry-Level Formal Manufacturing Data

We use data from UNIDO's INDSTAT2 database, which provides employment and value added statistics for a large range of countries at the ISIC two-digit level of disaggregation (UNIDO 2017). The industry statistics reported by INDSTAT2 database go back to the 1960s for several countries. The employment and value added data provided by INDSTAT2 covers up to 23 manufacturing industries for each country. We use this information to calculate labor productivity—value added per employee—and its growth rate over 10 yearly increments.

Since the latest possible year of observation in INDSTAT2 database is 2016 and about half the countries do report their industry statistics for 2016, we will primarily focus on 2015 as the final year of observation. To maximize the number of observations in our sample, we will use the panel dimension of the data by stacking five decades 1965–1975, 1975–1985, 1985–1995, 1995–2005, and

² Note that this specification controls for industry, period, and period $\times$ industry fixed effects, where for each country we include five decades 1965–1975, 1975–1985, 1985–1995, 1995–2005, and 2005–2015. In this specification, we do not include interaction terms for technology intensity that we explain in Section 4.

2005–2015 for all countries with data for at least one of those decades. Our sample covers a maximum of 100 countries. Although some developing countries do not have data for the earlier part of the sample, we have 75 developing countries with a wide range of geographical coverage in our sample. Appendix Table A1 provides a summary description of the list of countries and time period in our sample. Since some countries have gaps within these time periods, we also provide a breakdown of how many countries are included in each 10-year period in Appendix Table A2.

It is also important to note that UNIDO gathers data from industrial surveys, which differ in terms of types of firms covered across countries. While in most developed countries industrial surveys typically cover firms of all sizes, in developing countries they generally exclude firms with less than 5 or 10 employees. Hence, the sample excludes informal firms or micro-enterprises in developing countries, but does a good job of covering formal manufacturing industries across both developing and developed countries.

We use the technology intensity definition proposed by the OECD to categorize industries into three groups based on their R&D intensities (i.e. direct R&D expenditures as a percentage of gross output): low-, medium-, high-technology intensive industries. Since we expect industries that invest a higher portion of their output into research activities to generally invent and innovate new technologies, higher values of R&D intensity correspond to higher technology intensity. At the two-digit level, this classification includes the following industries in each category. The low-technology intensive industries include food products and beverages; tobacco products; textiles; wearing apparel and fur; leather and footwear; wood products; paper and paper products; printing and publishing; and recycling. The medium-technology intensive industries include coke, refined petroleum products and nuclear fuel; rubber and plastics products; other non-metallic mineral products; basic metals; fabricated metal products; electrical machinery and apparatus; motor vehicles, trailers and semi-trailers; chemicals and chemical products; machinery and equipment; other transport equipment. Finally, the high-technology intensive industries include office, accounting and computing machinery; radio, television and communications equipment; medical, precision and optical instruments.

3.2 Country-Level Manufacturing Data

We complement our industry-level analysis with a country-level analysis focusing on manufacturing employment and value added. The main source of data we use is the Groningen Growth and Development Center (GGDC, Timmer et al. 2014). The data covers 42 countries, including developed and developing ones, from the 1950s to early 2010s. The manufacturing value added includes constant-price series at

2005 prices. For further analysis, we incorporate data from a range of sources on manufacturing employment and output indicators, including the ILO, U.N., and World Bank. The downside of this data is that it starts earliest in the 1970s.

Finally, we use data from a number of sources to capture other time-varying, country-specific factors. First, we use data from *World Development Indicators* and Maddison (2009) on population, and GDP per capita. This data is used in our country-level analysis. Second, we use data from *Penn World Tables* on real exchange rates and related macroeconomic variables. This data is used in the robustness checks for the industry-level analysis.

4 Empirical Results

4.1 Baseline Specification

The sample includes a maximum of 100 countries and stacked decades from 1965 to 2015. We use a fixed-effects specification to estimate the convergence effect by regressing the growth rate of labor productivity on the log of initial labor productivity. Since we are interested in differential convergence by technology intensity across industries, our baseline specification takes the form:

$$\text{growth}_{ijt} = \alpha + \beta_1 \ln y_{ijt} + \beta_2 \ln y_{ijt} \times \text{LowTech} + \beta_3 \ln y_{ijt} \times \text{MedTech} + \sigma_{it} + \delta_i + \eta_j + \nu_t + u_{ijt} \quad (1)$$

where growth_{ijt} is the growth rate of labor productivity over a 10-year period in industry i , country j , at time period t ; $\ln y_{ijt}$ is the log of initial labor productivity at the beginning of the 10-year period; LowTech and MedTech are indicator variables for whether an industry is a low-technology or medium-technology intensive industry, respectively; σ_{it} are a set of industry $\times$ time period fixed effects that control for unobserved factors that affect each industry at a particular time period; δ_i are industry fixed effects that control for time-invariant heterogeneity at the industry level; η_j are country fixed effects that control for time-invariant heterogeneity at the country level; and ν_t are time period fixed effects that control for unobserved worldwide changes each year. The omitted category is high-technology intensive industries. We use OLS to estimate the model.

We are interested in the coefficient estimates β_1 , β_2 , and β_3 , which are measures of conditional convergence under the current specification, since we explicitly control for country-specific conditions using country fixed effects. More specifically, β_1 shows the conditional convergence parameter for high-technology intensive industries, β_2 shows whether there is a significant difference in

conditional convergence between high-technology and low-technology intensive industries, and β_3 shows whether there is a significant difference between high-technology and medium-technology intensive industries. To test for unconditional convergence, we exclude country fixed effects from the specification and check whether the estimated convergence parameters continue to be statistically significant and negative.

Since the value added reported for manufacturing industries in the UNIDO datasets is reported in nominal US\$ terms, the labor productivity (value added per employee) is also denominated in US\$ terms. The UNIDO data does not have any price deflators to be able to calculate real productivity changes at the industry level. Following Rodrik (2012), we will assume that there is a common global US\$ inflation rate for each industry combined with a random error term because the tradable nature of manufacturing industries implies that they face common world prices. If this assumption holds, the industry $\times$ period fixed effects will capture such prices changes, allowing us to isolate the convergence parameter for real productivity growth over time.³ In the robustness section, we will also test if the results hold using labor productivity measures adjusted for real exchange rate changes.

4.2 Primary Results: Convergence Patterns by Technology Intensity

Table 1 shows the results for Eq. (1) for the whole sample and for different country groups. The dependent variable in every specification is the compound annual growth rate of labor productivity for two-digit manufacturing industries. The explanatory variables of interest are the log of initial labor productivity and its interactions with technology intensity indicators, controlling for a range of fixed effects. We estimate each specification first without country fixed effects, which provide unconditional convergence coefficients. We then include country fixed effects and obtain conditional convergence estimates. We cluster standard errors at the country level to account for serial correlation in outcomes across countries.

The estimates in column (1) of Table 1 show the baseline results for the whole sample. The estimated unconditional convergence coefficient for high-technology intensive industries (reported in the first row) is 2.5% and significant at the 1% level. In the second row, we observe that the convergence coefficient for low-technology intensive industries is 0.8% smaller than that for high-technology intensive industries. In the third row, we find no evidence of a significant difference in convergence rates between medium- and high-technology intensive industries. Controlling for country

³ We omit the lengthy derivation to save space. Rodrik (2012) provides more details on this point.

Table 1: Unconditional convergence by technology intensity, 1965–2015.

	All			Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Log initial productivity	−0.025*** (0.004)	−0.063*** (0.005)	−0.038*** (0.005)	−0.060*** (0.009)	−0.011* (0.006)	−0.048*** (0.007)	−0.074*** (0.024)	−0.104*** (0.020)	−0.087*** (0.015)	−0.114*** (0.016)	
Base × low-technology intensive	0.007** (0.004)	0.006 (0.003)	0.017** (0.007)	0.014** (0.006)	−0.003 (0.007)	−0.001 (0.007)	0.049** (0.020)	0.049** (0.019)	0.050*** (0.011)	0.045*** (0.015)	
Base × medium-technology intensive	−0.002 (0.004)	−0.003 (0.003)	0.005 (0.006)	0.002 (0.004)	−0.018** (0.008)	−0.011* (0.006)	0.032 (0.020)	0.036* (0.019)	0.039** (0.013)	0.038** (0.015)	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Number of countries	100	100	26	26	18	18	20	20	14	14	
Number of observations	4904	4904	1808	1808	985	985	738	738	413	413	

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

fixed effects, the results presented in column (2) yield similar results, with a conditional convergence estimate of 6.3% and a smaller and imprecisely estimated interaction coefficient, implying a slower convergence rate for low-technology intensive industries compared to high-technology ones.

In terms of magnitude, a convergence rate of 2.5% a year in our baseline specification including all countries implies that high-technology intensive industries that are a tenth of the way to the technology frontier (approximately the bottom 20% of the industries in the sample) experience a convergence increase in their labor productivity growth of 5.8 percentage points per year ($0.025 \times \ln(10)$). For low-technology intensive industries, the same convergence increase in their labor productivity growth is 1.6 percentage points smaller ($0.007 \times \ln(10)$), resulting in a 4.1 percentage point annual growth in labor productivity.

Examining regional heterogeneity, the remaining columns of Table 1 indicate substantial differences across country groups. For Latin American and Sub-Saharan African economies, we observe that both low-technology and medium-technology intensive industries experience a significantly slower convergence in comparison to high-technology intensive ones. On the other hand, we find no evidence of a significant differential for low-technology industries' convergence in Asian economies, and if anything, we see that medium-technology intensive sectors experience a faster convergence than high-technology industries. In developed economies, we observe that while low-technology industries experience a slightly slower convergence, medium-technology industries converge at similar rates to high-technology industries.

Focusing on the magnitudes, a convergence rate of 7.4% a year in Latin American countries implies that high-technology intensive industries that are a tenth of the way to the technology frontier experience a convergence increase in their labor productivity growth of 17 percentage points per annum. This boost in convergence is 11.3 percentage points smaller for low-technology industries, resulting in a 5.8 percentage point annual growth in labor productivity. For medium-technology intensive industries, the convergence increase is 7.4 percentage points smaller (albeit less precisely estimated), yielding a labor productivity growth of 9.7 percentage points per year.⁴

These patterns can be explained by two main trends that have particularly become salient in the recent decades. First, the entry of highly competitive Asian

⁴ The estimates are similar for Sub-Saharan African economies. A convergence rate of 8.7% a year in Latin American countries implies that high-technology intensive industries that are a tenth of the way to the technology frontier experience a convergence increase in their labor productivity growth of 20 percentage points per annum. This increase in convergence is 11.5 percentage points smaller for low-technology industries, resulting in a 8.5 percentage point annual growth in labor productivity. For medium-technology intensive industries, the convergence increase is 9 percentage points smaller, resulting in a labor productivity growth of 11.1 percentage points per annum.

producers in the global markets has increased the competition faced by Latin American and Sub-Saharan African economies, out-competing them in several low- and medium-technology intensive sectors. This competitive pressure makes catching up with the technological frontier much harder as producers in Latin America and Sub-Saharan Africa keep losing market share in world markets. This is also evident for developed country producers of low-technology manufactured goods. Second, the skill-biased technological change and increased automation enabled advanced countries to keep their labor productivity high in sectors with higher technology intensity, while countries that were not successful in transferring technologies failed to achieve significant catch-up in low- and medium-technology industries.

4.3 Convergence Patterns Over Time

In the next step, we examine whether the rate of convergence across industries varies over time. In particular, we test whether the differential convergence patterns we observe emerge during the period of global integration, which exposed developing economies to increased competition both from advanced markets and also from fast industrializers within the developing world. The evidence presented in Tables 2 and 3 allow us to compare the period of globalization from 1985 to 2015 with the earlier period from 1965 to 1985. We find that for the most part, the differential convergence patterns emerge in post-1985 period, and we find no evidence of a significant difference across industries before the onset of global integration.

A related explanation for why we observe differential convergence across industries in certain regions could be that these economies might have experienced premature deindustrialization (Felipe, Mehta, and Rhee 2019; Haraguchi, Cheng, and Eveline Smeets 2017; Rodrik 2016; Tregenna 2009, 2011). That is, given their income levels and population levels, one would have expected these economies to continue increasing their industrial employment as a share of their total employment; however, due to both technological shocks that make it more difficult to reach the technological frontier and due to increased global competition from more advanced and newly emerging economies, the developing countries particularly in Latin America and Sub-Saharan Africa may have started deindustrializing at earlier income levels (Tregenna 2011).

To examine this potential channel, we test whether differential convergence emerges after the peak of manufacturing employment (as a share of total employment) has been reached. Table 4 presents the results. We find strong evidence that the low- and medium-technology industries begin to converge at slower rates in Latin America and Sub-Saharan Africa after the employment deindustrialization begins to take place. This is also the case for low-technology intensive industries in developed economies. In contrast, the findings presented in Table 5

Table 2: Unconditional convergence during global integration, 1985–2015.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	−0.029*** (0.005)	−0.071*** (0.007)	−0.045*** (0.007)	−0.071*** (0.010)	−0.017** (0.008)	−0.060*** (0.013)	−0.097** (0.036)	−0.116*** (0.025)	−0.104*** (0.014)	−0.125*** (0.021)
Base × low-technology	0.010** (0.004)	0.006* (0.003)	0.020** (0.009)	0.015** (0.007)	−0.000 (0.007)	0.001 (0.007)	0.076** (0.030)	0.068** (0.026)	0.050*** (0.012)	0.033 (0.019)
Base × medium-technology	0.002 (0.005)	−0.001 (0.003)	0.009 (0.007)	0.002 (0.005)	−0.014 (0.010)	−0.007 (0.006)	0.052 (0.031)	0.049* (0.028)	0.050*** (0.015)	0.044** (0.015)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	82	82	26	26	16	16	15	15	10	10
Number of observations	2860	2860	1090	1090	575	575	370	370	216	216

The table presents evidence on unconditional convergence using regression results from Eq. (1). The sample only includes the period 1985–2015. Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table 3: Unconditional convergence prior to global integration, 1965–1985.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.012** (0.005)	-0.052*** (0.008)	-0.018*** (0.006)	-0.038*** (0.012)	0.006 (0.007)	-0.024* (0.013)	-0.039** (0.015)	-0.072*** (0.017)	-0.012 (0.033)	-0.080 (0.044)
Base × low-technology intensive	-0.001 (0.006)	0.003 (0.006)	0.004 (0.007)	0.006 (0.008)	-0.008 (0.011)	-0.004 (0.011)	0.011 (0.020)	0.015 (0.018)	-0.002 (0.033)	0.049 (0.042)
Base × medium-technology intensive	-0.013** (0.006)	-0.009 (0.006)	-0.008 (0.008)	-0.007 (0.007)	-0.024* (0.012)	-0.020 (0.012)	-0.001 (0.017)	0.009 (0.016)	-0.017 (0.040)	0.021 (0.046)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	76	76	22	22	15	15	15	15	10	10
Number of observations	2044	2044	718	718	410	410	368	368	197	197

The table presents evidence on unconditional convergence using regression results from Eq. (1). The sample only includes the period 1965–1985. Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table 4: Unconditional convergence after employment deindustrialization.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.024*** (0.004)	-0.066*** (0.006)	-0.042*** (0.006)	-0.070*** (0.009)	-0.014* (0.007)	-0.054*** (0.010)	-0.065*** (0.019)	-0.092*** (0.013)	-0.097*** (0.014)	-0.126*** (0.019)
Base × low-technology intensive	0.007 (0.004)	0.005 (0.004)	0.021** (0.008)	0.016** (0.006)	-0.000 (0.009)	0.002 (0.009)	0.033 (0.019)	0.040** (0.019)	0.054*** (0.011)	0.043** (0.015)
Base × medium-technology intensive	-0.002 (0.005)	-0.003 (0.003)	0.010 (0.007)	0.004 (0.004)	-0.016 (0.011)	-0.009 (0.006)	0.025 (0.015)	0.035** (0.014)	0.047*** (0.014)	0.045** (0.018)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	86	86	26	26	17	17	16	16	12	12
Number of observations	3691	3691	1636	1636	689	689	505	505	287	287

The table presents evidence on unconditional convergence using regression results from Eq. (1). The sample includes observations for each country after which the peak of employment share of manufacturing is reached. Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table 5: Unconditional convergence before employment deindustrialization.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.046*** (0.015)	-0.081*** (0.013)	-0.043** (0.013)	-0.035 (0.028)	-0.021 (0.017)	-0.058*** (0.018)	-0.097*** (0.036)	-0.098*** (0.029)	-0.085 (0.074)	-0.162 (0.098)
Base × low-technology intensive	0.020 (0.013)	0.017 (0.011)	0.007 (0.015)	0.011 (0.022)	-0.002 (0.014)	-0.001 (0.013)	0.086* (0.042)	0.054 (0.033)	0.060 (0.071)	0.119 (0.098)
Base × medium-technology intensive	0.010 (0.014)	0.008 (0.013)	-0.021 (0.015)	-0.020 (0.019)	-0.012 (0.022)	-0.007 (0.022)	0.047 (0.038)	0.020 (0.029)	0.031 (0.074)	0.084 (0.100)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	52	52	7	7	12	12	10	10	7	7
Number of observations	1213	1213	172	172	296	296	233	233	126	126

The table presents evidence on unconditional convergence using regression results from Eq. (1). The sample includes observations for each country before which the peak of employment share of manufacturing is reached. Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

show no evidence that differential convergence takes place before the peak of manufacturing employment is reached.

4.4 Convergence Patterns by Comparative Advantage

Finally, we test for whether these differences across country groups can be explained by their comparative advantage. In particular, we would expect that countries specialized in producing manufactured goods due to their comparative advantage to perform better in terms of unconditional convergence in manufacturing. In Table 6, we compare the results for manufactures exporters to non-manufactures exporters. In particular, we use two definitions for manufactures exporters: (1) if manufactured exports as a share of total exports exceeds 75%, and (2) if the share of manufactures exports is greater than the share of manufactures imports, then we consider this economy as a manufactures exporter. Despite slightly different categorizations, these results are consistent with the interpretation that differential convergence, particularly for low-technology intensive manufactures, is significant for the non-manufactures exporters; whereas for manufactures exporters, the low- and medium-technology industries experience at least as high convergence rates as the high-technology industries (and even higher for the medium-technology group). Overall, these results confirm that specialization patterns driven by comparative advantage matter for explaining underlying trends in differential convergence by technology intensity.

4.5 Robustness Checks

In this section, we present several robustness checks to test the sensitivity of our primary results presented in Table 1. First, one concern could be that if countries experience sustained changes in their real exchange rate, changes in value added denominated in U.S. dollars may be systematically biased. This would not happen as long as increases in domestic costs are offset by a depreciation of the home currency, without changing the dollar values. If, however, exchange rates do not adjust as they should, then the measured changes in productivity expressed in U.S. dollars can be misleading. In particular, if low-income countries that have a high-share of low-productivity industries experience real exchange rate appreciations (such that a rise in domestic costs not being compensated by nominal depreciation), this would lead to an upward bias in convergence estimates.

To check the robustness of our results to this concern, Table 7 presents regressions where we use a measure of labor productivity growth that is adjusted

Table 6: Results by manufacturing specialization.

(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Manufactures exporters		Manufactures exporters		Share of manuf. exports > share of manuf. imports		Manufactured exports < 75%		Non-manufactures exporters		Share of manuf. exports < share of manuf. imports			
Log initial productivity	-0.015*** (0.004)	-0.048*** (0.005)	-0.014*** (0.004)	-0.049*** (0.005)	-0.037*** (0.008)	-0.076*** (0.008)	-0.035*** (0.007)	-0.074*** (0.007)						
Base × low-technology intensive	0.001 (0.005)	0.001 (0.005)	0.001 (0.004)	0.000 (0.005)	0.016*** (0.007)	0.013** (0.005)	0.015** (0.006)	0.012** (0.005)						
Base × medium-technology intensive	-0.005 (0.004)	-0.006* (0.003)	-0.007* (0.004)	-0.008** (0.003)	0.005 (0.007)	0.004 (0.006)	0.005 (0.007)	0.003 (0.005)						
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes						
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes						
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes						
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes						
Number of countries	36	36	37	37	64	64	63	63						
Number of observations	2256	2256	2180	2180	2648	2648	2724	2724						

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table 7: Robustness check using a real exchange rate adjusted growth rate.

	All			Developed			Asia			Latin America			Sub-Saharan Africa		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)					
Log initial productivity	-0.022*** (0.004)	-0.056*** (0.006)	-0.033*** (0.005)	-0.055*** (0.010)	-0.009 (0.006)	-0.042*** (0.007)	-0.080*** (0.023)	-0.101*** (0.022)	-0.085*** (0.018)	-0.107*** (0.022)					
Base × low-technology intensive	0.008** (0.004)	0.008** (0.004)	0.018*** (0.006)	0.015*** (0.005)	-0.002 (0.006)	0.000 (0.006)	0.049** (0.020)	0.058** (0.021)	0.058*** (0.012)	0.058*** (0.016)					
Base × medium-technology intensive	-0.001 (0.004)	-0.001 (0.003)	0.006 (0.005)	0.004 (0.004)	-0.015* (0.008)	-0.008 (0.005)	0.033 (0.021)	0.037 (0.023)	0.041** (0.017)	0.045** (0.017)					
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes					
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes					
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes					
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes					
Number of countries	86	86	25	25	17	17	17	17	11	11					
Number of observations	3916	3916	1366	1366	921	921	617	617	327	327					

The table presents evidence on unconditional convergence using regression results from Eq. (1). The dependent variable is growth rate of labor productivity adjusted for real exchange rate changes. Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

for real exchange rate changes. In particular, following Rodrik (2012), we deflated the growth rate of value added per worker by the real exchange rate appreciation of the country where the industry is located in. As a result of this adjustment, the productivity growth rates of industries have been reduced in countries that have experienced a real exchange rate appreciation, and vice versa. The results presented in Table 7 are entirely consistent with our results in Table 1.

Another concern could be that the results might be driven by countries with very few industries represented in the dataset. This could be particularly a concern for small developing countries that do not have observations for all industries covered in the data. To test the robustness of our results, we reestimate our baseline results by excluding countries with less than 10 industries. The results provided in Table 8 show that the convergence estimates remain very similar, indicating that this potential concern is not a source of bias in this case.

Moreover, we have so far clustered standard errors at the country level. One concern could be that there might be serial correlation across outcomes at the industry level. In Table 9, we reestimate our baseline results by clustering standard errors at the industry level. We observe that the convergence estimates remain significant in this specification, and if anything, the significance increases for most estimates. We conclude that clustering at the country level is in fact more conservative for the precision of our estimates.

In addition, we also test whether the results are driven by an unbalanced sample that includes the largest possible number of observations. In Appendix Table A3, we restrict the sample to a common list of countries with the necessary data. The estimates are quite similar to those reported in Table 1.

Another robustness check that we conduct is to examine whether our results are driven by extreme values of growth rates. In Appendix Table A4, we exclude observations with the lowest 10% of values for growth, and in Appendix Table A5, we exclude observations with the highest 10% of values for growth. In both of these restricted samples, the estimates are consistent with our primary results.

Moreover, we test whether the results are driven by particular country groups. In Appendix Table A6, we exclude the former socialist countries from the sample, and in Appendix Table A7, we exclude the OECD countries. In the latter case, since all developed countries are OECD countries, we drop reporting estimates for this category. In both sets of results, we observe that the estimates remain consistent with our main results.

Furthermore, we drop industry controls, including industry fixed effects and period-industry fixed effects, keeping country fixed effects in the same specifications as we did before. In Appendix Table A8, we observe similar, but muted effects, indicating that the effects we observe in our main specification are within industry effects,

Table 8: Robustness check excluding countries with less than 10 industries.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.024*** (0.004)	-0.062*** (0.005)	-0.038*** (0.005)	-0.059*** (0.009)	-0.011* (0.006)	-0.048*** (0.007)	-0.073*** (0.024)	-0.102*** (0.019)	-0.080*** (0.020)	-0.111*** (0.017)
Base × low-technology	0.007* (0.004)	0.005 (0.004)	0.017** (0.007)	0.014** (0.006)	-0.003 (0.007)	-0.001 (0.007)	0.048** (0.019)	0.046** (0.018)	0.046** (0.016)	0.047** (0.016)
Base × medium-technology	-0.003 (0.004)	-0.003 (0.003)	0.005 (0.006)	0.002 (0.004)	-0.018** (0.009)	-0.012* (0.006)	0.031 (0.020)	0.035* (0.019)	0.032* (0.015)	0.035* (0.016)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	96	96	26	26	18	18	19	19	12	12
Number of observations	4786	4786	1793	1793	968	968	713	713	393	393

The table presents evidence on unconditional convergence using regression results from Eq. (1). The sample excludes countries with less than 10 industries. Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table 9: Robustness check clustering standard errors at the industry level.

	All			Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Log initial productivity	-0.025*** (0.003)	-0.063*** (0.004)	-0.038*** (0.011)	-0.060*** (0.010)	-0.011 (0.007)	-0.048*** (0.008)	-0.074** (0.027)	-0.104*** (0.025)	-0.087*** (0.005)	-0.114*** (0.006)	
Base × low-technology intensive	0.007** (0.003)	0.006 (0.003)	0.017 (0.011)	0.014 (0.010)	-0.003 (0.007)	-0.001 (0.008)	0.049* (0.028)	0.049* (0.026)	0.050*** (0.007)	0.045*** (0.012)	
Base × medium-technology intensive	-0.002 (0.005)	-0.003 (0.003)	0.005 (0.012)	0.002 (0.009)	-0.018 (0.012)	-0.011 (0.009)	0.032 (0.028)	0.036 (0.025)	0.039*** (0.013)	0.038*** (0.013)	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Number of countries	100	100	26	26	18	18	20	20	14	14	
Number of observations	4904	4904	1808	1808	985	985	738	738	413	413	

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the industry level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

accounting for time-invariant characteristics of industries and time-specific shocks that industries experience.

Besides, we estimate a weighted regression by using the size of the industry as weights. In Appendix Table A9, we use the log of value added at the industry level to estimate a weighted regression. The results are very similar to our main estimates, indicating that our estimates are not driven by the small industries.

In addition, we use growth rates calculated from log-linear trend using 10 annual observations instead of only using the endpoints. One advantage of using these growth rates is that they prevent the introduction of a spurious bias from having lagged labor productivity appearing on both right and left side of the specification. The results presented in Appendix Table A10 are again very similar to our main estimates.

Another concern with our estimates could be that they reflect regional disparities as opposed to global ones since we have reported regions separately. To address this issue, we reestimate differential convergence rates by using a fully interacted specification with regional dummy variables using the full sample. Appendix Table A11 provides region-specific differential convergence rates. Including country fixed effects, we continue to observe larger positive coefficients for low-technology and medium-technology intensive products for Latin America and Sub-Saharan Africa.

To consider the robustness of our results for across time periods, we use an alternative time period split, taking 1995 as the break point (instead of 1985). One could argue that globalization gained momentum after 1995. Appendix Table A12 reports estimates from 1965 to 1995, while Appendix Table A13 reports them from 1995 to 2015. We observe that the differential effects appear for Latin America in the earlier time period, and become slightly muted in the latter period. For Sub-Saharan Africa, on the other hand, we observe strong effects in the latter part of the sample, in the post-1995 period. These patterns are consistent with the fact that opening to international trade began to occur earlier for many Latin American countries than those in Sub-Saharan Africa (Bates, Coatsworth, and Williamson 2007; Belli 1991).

Finally, we examine the potential heterogeneity among different product groups. In Appendix Table A14, we examine heterogeneity among low-technology intensive products. In particular, we group these products into three categories: (i) textiles, clothing, and footwear, (ii) food, beverages, and tobacco, (iii) wood, paper, and recycling. While the differential convergence coefficients for food, beverages, and tobacco appear larger than those for textiles, clothing, and footwear, and wood, paper, and recycling for Latin America and Sub-Saharan Africa, the differences are small and not statistically significant in most cases. In a similar vein, in Appendix Table A15, we focus on heterogeneity among medium-technology intensive products by dividing them into four categories: (i) petroleum, chemicals, and plastics, (ii) iron, steel, and metal products, (iii) machinery

and equipment, and (iv) transport equipment. The differential convergence coefficients are particularly large for petroleum, chemicals, and plastics for Latin America and Sub-Saharan Africa, while those for machinery and equipment for Sub-Saharan Africa and transport equipment for Latin America appear also large and significant. However, the differences among products are in most cases small in magnitude and not statistically significant.

5 Conclusion

The main objective of this paper is to provide evidence on whether unconditional convergence within manufacturing industries varies by the technology intensity of the industry. Using a comprehensive panel dataset from 1965 to 2015 in 10-year period intervals for 100 countries, we test whether there is any evidence of differential convergence depending on the level of technology intensity. While previous studies have established strong evidence for unconditional convergence for manufacturing industries as a whole, there is no evidence as to whether such convergence systematically differs by technology intensity. The key contribution of this paper is the assessment of the differential convergence effects by technology intensity both across different country groups and different time periods, with the goal of understanding the underlying factors that give rise to such effects.

We find that there are systematic difference in unconditional convergence across industries. For Latin American and Sub-Saharan African countries, we find that low-technology and medium-technology intensive industries experience a significantly slower convergence in comparison to high-technology intensive ones. In contrast, we find no evidence of a significant differential for low-technology industries' convergence in Asian economies, and if anything, we observe the opposite that medium-technology intensive sectors experience a faster convergence than high-technology industries. In developed economies, we find that while low-technology industries experience a slightly slower convergence, medium-technology industries converge at similar rates to high-technology industries. We also find that these differences emerge during the period of increased global integration, which exposed developing economies to increased competition both from advanced markets and fast industrializers within the developing world. Our findings show that differential convergence patterns are stronger after the peak of manufacturing employment share has been reached. Finally, we find that specialization patterns driven by comparative advantage play an important role in explaining patterns of differential convergence by technology intensity.

Our findings have important policy implications for developing countries, particularly for those that focus on manufacturing as an engine of economic

development. The new technologies that embody skill-biased technological change are likely to keep posing new challenges for catching up with the technological frontier that is extended at a greater pace, particularly in relatively more labor-intensive sectors most of which also tend to be low- and medium-technology intensive. Moreover, these industries are also more prone to increased global competition by new entrants from relatively lower-cost economies. Under these circumstances, an industrial policy that is focused on exploiting the convergence potential in manufacturing industries can only be viable if it successfully incentivizes technological upgrading from lower- to higher-technology intensive industries. This is crucial for remaining competitive as wages increase over the course of development, and for delaying premature industrialization to reap the full benefits of a mature industrial economy before the share of services begins to rise.

Appendix: Additional tables

Table A1: List of countries and time period.

Country	Time period	Country	Time period
Algeria	1972–2017	Kuwait	1967–2017
Argentina	1963–2002	Latvia	1986–2016
Australia	1963–2017	Libya	1964–1980
Austria	1963–2017	Luxembourg	1985–2017
Bangladesh	1967–2011	Madagascar	1967–2006
Barbados	1970–1997	Malawi	1964–2012
Belgium	1963–2017	Malaysia	1968–2017
Bolivia	1970–2014	Malta	1963–2017
Brazil	1963–2017	Mauritius	1968–2017
Canada	1963–2017	Mexico	1984–2017
Central African Republic	1973–1993	Mongolia	1990–2017
Chile	1963–2017	Morocco	1976–2015
China	1977–2017	Netherlands	1963–2017
China, Hong Kong SAR	1973–2008	New Zealand	1963–2017
China, Macao SAR	1978–2016	Nicaragua	1963–1985
Colombia	1963–2017	Nigeria	1963–1996
Costa Rica	1963–2017	Norway	1963–2017
Cyprus	1963–2017	Occupied Palestinian Territory	1994–2017
Czech Republic	1987–2017	Oman	1993–2017
Czechoslovakia	1963–1991	Pakistan	1963–2006
Denmark	1963–2017	Panama	1963–2017
Dominican Republic	1963–2016	Papua New Guinea	1963–2001
Ecuador	1963–2017	Peru	1974–2017

Table A1: (continued)

Country	Time period	Country	Time period
Egypt	1964–2017	Philippines	1963–2017
El Salvador	1963–1998	Poland	1963–2017
Eritrea	1992–2016	Portugal	1963–2017
Ethiopia	1990–2015	Republic of Korea	1963–2017
Ethiopia and Eritrea	1965–1989	Romania	1963–2017
Fiji	1968–2016	Russian Federation	1993–2017
Finland	1963–2017	Senegal	1974–2014
France	1963–2017	Singapore	1963–2017
Germany, Fed. Rep	1963–1990	Slovakia	1991–2017
Germany	1991–2017	Slovenia	1987–2017
Ghana	1963–2003	South Africa	1963–2017
Greece	1963–2017	Spain	1963–2017
Guatemala	1968–2006	Swaziland	1967–2014
Honduras	1963–1996	Sweden	1963–2017
Hungary	1963–2017	Syrian Arab Republic	1963–2010
Iceland	1967–2017	Taiwan	1973–2017
India	1963–2017	Macedonia	1987–2017
Indonesia	1970–2017	Trinidad and Tobago	1966–2006
Iran	1963–2017	Tunisia	1963–2017
Iraq	1963–2017	Turkey	1963–2017
Ireland	1963–2017	United Kingdom	1963–2017
Israel	1963–2017	United Republic of Tanzania	1965–2017
Italy	1967–2017	United States of America	1963–2017
Jamaica	1963–2006	Uruguay	1968–2014
Japan	1963–2017	Venezuela	1963–1998
Jordan	1963–2017	Yugoslavia	1963–1989
Kenya	1963–2017	Zambia	1963–2015

The table provides the list of countries in our sample together with the time coverage for each country, including the beginning and end dates of data.

Table A2: Time period and number of countries.

Time period	Number of countries
1965–1975	83
1975–1985	89
1985–1995	100
1995–2005	93
2005–2015	85

This table provides the number of countries we have data on key indicators for the different time periods.

Table A3: Robustness check using a common sample.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.020*** (0.005)	-0.057*** (0.007)	-0.041*** (0.007)	-0.065*** (0.011)	-0.012* (0.006)	-0.044*** (0.007)	-0.083*** (0.020)	-0.098*** (0.018)	-0.090** (0.025)	-0.130*** (0.025)
Base × low-technology intensive	0.005 (0.004)	0.005 (0.004)	0.023** (0.009)	0.020*** (0.007)	0.002 (0.007)	0.003 (0.008)	0.047* (0.021)	0.048* (0.024)	0.049 (0.027)	0.069** (0.023)
Base × medium-technology intensive	-0.003 (0.004)	-0.005 (0.003)	0.008 (0.009)	0.004 (0.005)	-0.005 (0.007)	-0.004 (0.005)	0.024 (0.015)	0.026 (0.015)	0.017 (0.029)	0.040 (0.022)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	62	62	22	22	14	14	10	10	7	7
Number of observations	3813	3813	1679	1679	873	873	445	445	265	265

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A4: Robustness check excluding observations with the lowest 10% values for growth.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.024*** (0.004)	-0.050*** (0.005)	-0.036*** (0.005)	-0.054*** (0.008)	-0.012* (0.007)	-0.041*** (0.007)	-0.045*** (0.012)	-0.066*** (0.009)	-0.086** (0.031)	-0.103*** (0.021)
Base × low-technology	0.007* (0.004)	0.007** (0.003)	0.016** (0.006)	0.015** (0.006)	0.002 (0.008)	0.003 (0.007)	0.014 (0.011)	0.017* (0.009)	0.055* (0.027)	0.059** (0.020)
Base × medium-technology	-0.003 (0.004)	-0.002 (0.004)	0.005 (0.006)	0.003 (0.004)	-0.013 (0.009)	-0.008 (0.008)	0.002 (0.011)	0.008 (0.010)	0.061** (0.025)	0.056*** (0.018)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	100	100	26	26	18	18	20	20	14	14
Number of observations	4355	4355	1689	1689	882	882	634	634	303	303

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A5: Robustness check excluding observations with the highest 10% values for growth

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.011*** (0.003)	-0.043*** (0.004)	-0.025*** (0.004)	-0.040*** (0.006)	-0.001 (0.003)	-0.029*** (0.004)	-0.066** (0.027)	-0.093*** (0.024)	-0.026 (0.035)	-0.064* (0.032)
Base × low-technology intensive	0.001 (0.003)	0.001 (0.003)	0.008** (0.003)	0.004 (0.004)	-0.004 (0.003)	-0.001 (0.005)	0.046* (0.024)	0.047* (0.023)	0.010 (0.030)	0.015 (0.028)
Base × medium-technology intensive	-0.001 (0.003)	-0.003 (0.002)	0.001 (0.003)	-0.004 (0.003)	-0.007*** (0.002)	-0.006* (0.003)	0.038 (0.023)	0.040* (0.023)	-0.005 (0.034)	0.009 (0.034)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	100	100	26	26	18	18	20	20	14	14
Number of observations	4486	4486	1683	1683	867	867	674	674	367	367

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A6: Robustness check excluding former socialist countries.

	All			Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Log initial productivity	-0.021*** (0.004)	-0.061*** (0.006)	-0.043*** (0.010)	-0.060*** (0.012)	-0.011* (0.006)	-0.048*** (0.007)	-0.074*** (0.024)	-0.104*** (0.020)	-0.087*** (0.015)	-0.114*** (0.016)	
Base × low-technology intensive	0.005 (0.004)	0.004 (0.004)	0.018 (0.011)	0.016* (0.009)	-0.003 (0.007)	-0.001 (0.007)	0.049** (0.020)	0.049** (0.019)	0.050*** (0.011)	0.045*** (0.015)	
Base × medium-technology intensive	-0.004 (0.004)	-0.005 (0.003)	0.004 (0.011)	0.002 (0.008)	-0.018* (0.009)	-0.011* (0.006)	0.032 (0.020)	0.036* (0.019)	0.039** (0.013)	0.038** (0.015)	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Number of countries	95	95	23	23	17	17	20	20	14	14	
Number of observations	4675	4675	1643	1643	960	960	738	738	413	413	

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A7: Robustness check excluding OECD countries.

	All		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log initial productivity	-0.042*** (0.008)	-0.073*** (0.008)	-0.010 (0.012)	-0.048*** (0.010)	-0.074*** (0.024)	-0.104*** (0.020)	-0.087*** (0.015)	-0.114*** (0.016)
Base × low-technology intensive	0.015** (0.007)	0.013** (0.006)	-0.007 (0.012)	-0.001 (0.012)	0.049** (0.020)	0.049** (0.019)	0.050*** (0.011)	0.045*** (0.015)
Base × medium-technology intensive	0.005 (0.007)	0.006 (0.006)	-0.028** (0.011)	-0.014 (0.010)	0.032 (0.020)	0.036* (0.019)	0.039** (0.013)	0.038** (0.015)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	75	75	14	14	20	20	14	14
Number of observations	3116	3116	705	705	738	738	413	413

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A8: Robustness check excluding industry controls.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.017*** (0.002)	-0.032*** (0.003)	-0.021*** (0.003)	-0.025*** (0.004)	-0.017** (0.006)	-0.029*** (0.005)	-0.015*** (0.005)	-0.019*** (0.004)	-0.037*** (0.011)	-0.043*** (0.016)
Base × low-technology intensive	0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Base × medium-technology intensive	0.001*** (0.000)	0.002*** (0.000)	0.000* (0.000)	0.001** (0.000)	0.001 (0.001)	0.002** (0.001)	0.002** (0.001)	0.003*** (0.001)	0.003** (0.001)	0.003* (0.002)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	No	No	No	No	No	No	No	No	No	No
Period fixed effects	No	No	No	No	No	No	No	No	No	No
Number of countries	100	100	26	26	18	18	20	20	14	14
Number of observations	4904	4904	1808	1808	985	985	738	738	413	413

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A9: Robustness check using log of value added as weights.

	All			Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Log initial productivity	-0.024*** (0.004)	-0.061*** (0.005)	-0.039*** (0.005)	-0.060*** (0.009)	-0.013* (0.006)	-0.049*** (0.007)	-0.067*** (0.019)	-0.096*** (0.015)	-0.084*** (0.015)	-0.111*** (0.015)	
Base × low-technology intensive	0.007* (0.003)	0.005 (0.003)	0.017** (0.007)	0.014** (0.006)	-0.001 (0.007)	0.001 (0.007)	0.042*** (0.014)	0.041*** (0.014)	0.047*** (0.011)	0.043*** (0.014)	
Base × medium-technology intensive	-0.002 (0.004)	-0.003 (0.003)	0.006 (0.006)	0.003 (0.004)	-0.015* (0.008)	-0.009* (0.005)	0.024 (0.015)	0.029* (0.015)	0.037** (0.013)	0.037** (0.014)	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Number of countries	100	100	26	26	18	18	20	20	14	14	
Number of observations	4904	4904	1808	1808	985	985	738	738	413	413	

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A10: Robustness check using growth rates calculated from log-linear trend using 10 annual observations.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.019*** (0.004)	-0.052*** (0.005)	-0.029*** (0.003)	-0.047*** (0.008)	-0.004 (0.003)	-0.039*** (0.007)	-0.066*** (0.021)	-0.094*** (0.015)	-0.098*** (0.016)	-0.110*** (0.017)
Base × low-technology intensive	0.004 (0.004)	0.003 (0.003)	0.010** (0.004)	0.007* (0.003)	-0.008 (0.005)	-0.005 (0.006)	0.044** (0.017)	0.044*** (0.015)	0.067*** (0.013)	0.056*** (0.017)
Base × medium-technology intensive	-0.005 (0.005)	-0.006 (0.004)	0.001 (0.003)	-0.002 (0.003)	-0.026** (0.011)	-0.019** (0.008)	0.030* (0.017)	0.036** (0.015)	0.055*** (0.015)	0.046** (0.017)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	100	100	26	26	18	18	20	20	14	14
Number of observations	4904	4904	1808	1808	985	985	738	738	413	413

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A11: Robustness check focusing on region-specific differential effects in a fully interacted specification with full sample.

	All	
	(1)	(2)
Base × developed	−0.004** (0.002)	−0.046*** (0.008)
Base × Asia	−0.003 (0.002)	−0.027*** (0.009)
Base × Latin America	−0.007*** (0.002)	−0.054*** (0.006)
Base × Sub-Saharan Africa	−0.009*** (0.002)	−0.070*** (0.009)
Base × other	−0.006*** (0.002)	−0.061*** (0.007)
Base × developed × low-technology intensive	−0.000 (0.001)	0.001 (0.001)
Base × Asia × low-technology intensive	0.001 (0.001)	0.002* (0.001)
Base × Latin America × low-technology intensive	0.001 (0.001)	0.003** (0.001)
Base × Sub-Saharan Africa × low-technology intensive	0.001 (0.002)	0.002 (0.002)
Base × other × low-technology intensive	0.001 (0.001)	0.002 (0.001)
Base × developed × medium-technology intensive	−0.001 (0.001)	−0.000 (0.001)
Base × Asia × medium-technology intensive	−0.000 (0.001)	0.001** (0.001)
Base × Latin America × medium-technology intensive	0.000 (0.002)	0.003** (0.001)
Base × Sub-Saharan Africa × medium-technology intensive	0.000 (0.002)	0.004** (0.001)
Base × other × medium-technology intensive	0.001 (0.002)	0.002* (0.001)
Country fixed effects	No	Yes
Industry fixed effects	Yes	Yes
Period fixed effects	Yes	Yes
Period × industry fixed effects	Yes	Yes
Number of countries	100	100
Number of observations	4904	4904

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A12: Robustness check using an alternative time period split, 1965–1995.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.013** (0.006)	-0.052*** (0.006)	-0.022** (0.009)	-0.037*** (0.012)	0.011* (0.005)	-0.030*** (0.006)	-0.079** (0.033)	-0.112*** (0.026)	-0.063* (0.032)	-0.079*** (0.024)
Base × low-technology intensive	0.005 (0.005)	0.005 (0.005)	0.006* (0.003)	0.005 (0.005)	-0.004 (0.007)	-0.003 (0.009)	0.058* (0.029)	0.054** (0.025)	0.043 (0.027)	0.042 (0.026)
Base × medium-technology intensive	-0.006 (0.005)	-0.006 (0.005)	-0.008 (0.005)	-0.007 (0.005)	-0.016* (0.009)	-0.017* (0.008)	0.043 (0.029)	0.047* (0.025)	0.033 (0.031)	0.028 (0.026)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	86	86	23	23	17	17	19	19	12	12
Number of observations	2893	2893	968	968	604	604	575	575	273	273

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A13: Robustness check using an alternative time period split, 1995–2015.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.033*** (0.006)	-0.064*** (0.007)	-0.046*** (0.008)	-0.064*** (0.014)	-0.029*** (0.009)	-0.054*** (0.017)	-0.062*** (0.015)	-0.081*** (0.007)	-0.114*** (0.026)	-0.121*** (0.007)
Base × low-technology intensive	0.008* (0.005)	0.005 (0.004)	0.021** (0.010)	0.016* (0.008)	0.001 (0.009)	-0.001 (0.008)	0.023** (0.008)	0.035** (0.010)	0.052*** (0.012)	0.047* (0.022)
Base × medium-technology intensive	0.001 (0.006)	-0.002 (0.005)	0.012 (0.008)	0.006 (0.006)	-0.012 (0.010)	-0.008 (0.006)	-0.020 (0.017)	-0.009 (0.019)	0.053** (0.016)	0.052*** (0.012)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	66	66	25	25	14	14	6	6	6	6
Number of observations	2011	2011	840	840	381	381	163	163	140	140

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A14: Heterogeneity within low-technology intensive products.

	All			Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	
Log initial productivity	-0.025*** (0.004)	-0.063*** (0.005)	-0.038*** (0.005)	-0.061*** (0.009)	-0.011* (0.006)	-0.049*** (0.007)	-0.074*** (0.024)	-0.105*** (0.020)	-0.087*** (0.015)	-0.115*** (0.016)	
Base × textiles, clothing, footwear	0.010** (0.004)	0.005 (0.004)	0.014** (0.007)	0.010* (0.005)	-0.008 (0.007)	-0.008 (0.005)	0.045** (0.020)	0.045** (0.018)	0.049* (0.023)	0.034 (0.024)	
Base × food, beverages, tobacco	0.006 (0.005)	0.011* (0.006)	0.027*** (0.007)	0.028*** (0.007)	0.005 (0.008)	0.013 (0.011)	0.062*** (0.020)	0.068*** (0.020)	0.054*** (0.015)	0.064*** (0.020)	
Base × wood, paper, recycling	0.007* (0.004)	0.003 (0.003)	0.010 (0.007)	0.004 (0.005)	-0.006 (0.006)	-0.007 (0.006)	0.041* (0.021)	0.035* (0.019)	0.044** (0.016)	0.030* (0.016)	
Base × medium-technology intensive	-0.002 (0.004)	-0.003 (0.003)	0.005 (0.006)	0.002 (0.004)	-0.018* (0.008)	-0.011* (0.006)	0.032 (0.020)	0.036* (0.019)	0.039** (0.013)	0.038** (0.015)	
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Number of countries	100	100	26	26	18	18	20	20	14	14	
Number of observations	4904	4904	1808	1808	985	985	738	738	413	413	

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

Table A15: Heterogeneity within low-technology intensive products.

	All		Developed		Asia		Latin America		Sub-Saharan Africa	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log initial productivity	-0.025*** (0.004)	-0.063*** (0.005)	-0.038*** (0.005)	-0.060*** (0.009)	-0.011* (0.006)	-0.048*** (0.007)	-0.074*** (0.024)	-0.105*** (0.020)	-0.087*** (0.015)	-0.113*** (0.016)
Base × low-technology intensive	0.007** (0.004)	0.006 (0.003)	0.017** (0.007)	0.014** (0.006)	-0.003 (0.007)	-0.001 (0.007)	0.049** (0.020)	0.049** (0.019)	0.050*** (0.011)	0.045*** (0.015)
Base × petroleum, chemicals, plastics	-0.001 (0.006)	0.001 (0.004)	0.003 (0.007)	-0.000 (0.005)	-0.023** (0.010)	-0.012 (0.007)	0.042* (0.023)	0.046* (0.023)	0.048*** (0.012)	0.047*** (0.015)
Base × iron, steel, metal products	-0.001 (0.004)	-0.006 (0.004)	0.010 (0.008)	0.005 (0.005)	-0.017* (0.009)	-0.014** (0.006)	0.029 (0.025)	0.034 (0.023)	0.024 (0.013)	0.026* (0.014)
Base × machinery and equipment	-0.001 (0.004)	-0.004 (0.004)	0.007 (0.005)	0.004 (0.004)	-0.010 (0.007)	-0.004 (0.006)	0.004 (0.022)	0.006 (0.018)	0.062*** (0.019)	0.045*** (0.019)
Base × transport equipment	-0.006 (0.007)	-0.009 (0.006)	0.005 (0.006)	0.002 (0.005)	0.001 (0.012)	-0.010 (0.009)	0.030 (0.022)	0.037* (0.020)	0.021 (0.031)	0.028 (0.031)
Country fixed effects	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period × industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of countries	100	100	26	26	18	18	20	20	14	14
Number of observations	4904	4904	1808	1808	985	985	738	738	413	413

The table presents evidence on unconditional convergence using regression results from Eq. (1). Robust standard errors are clustered at the country level. ***, **, * denote significance at the 1, 5, and 10% levels, respectively.

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