Labour Productivity Convergence in Manufacturing: Historical Patterns and Sub-Sectoral Heterogeneity*

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Abstract. This paper investigates the extent to which manufacturing exhibits labour productivity convergence. Drawing on a newly harmonised dataset covering 175 countries and 12 manufacturing sub-sectors over six decades (1963-2019), the results support the β-convergence hypothesis, pointing to a significant and robust negative relationship between initial productivity levels and subsequent growth rates. This convergence effect is broad-based across manufacturing sub-sectors and strengthens over time, particularly from the 1990s onward. Taken together, these findings lend support to the view that reallocating factors of production towards manufacturing sub-sectors may generate substantial economy-wide gains. At the same time, dispersion in productivity levels in 2019 happened to be exactly the same as in 1963. A breakdown of this result reveals substantial variation over time, suggesting that a short decade of uneven productivity dynamics (1983-1993) was sufficient to generate such a marked increase in dispersion that reversing it required nearly three decades (1993-2019). This latter period was thus the only one during which both β-convergence and σ-convergence went hand in hand.

Keywords: Labour productivity, manufacturing, convergence, economic growth.

JEL Codes: L60, O14, O50.

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1 Introduction

In recent years, industrial policies have regained prominence in both policy circles and academic debates (Chang and Andreoni, 2020; Juhász and Lane, 2024). This resurgence has renewed interest not only in exploring patterns of structural change, but also in assessing the extent to which manufacturing continued to serve as the leading sector underpinning economy-wide productivity growth (Kaldor, 1966; Abramovitz, 1986; Rodrik, 2013). At the core of this focus lies one of the oldest and perhaps most influential tenets of the development literature: that economic development entails structural transformation, with industrialisation being its pivotal stage (Kuznets, 1973; Allen, 2011; Szirmai, 2012). Historically, industrialisation has indeed underpinned the growth of today's advanced economies, with manufacturing's share of output and employment initially rising — as surplus labour shifted out of agriculture — and subsequently declining as countries developed and transitioned towards services (Clark, 1940; Lewis, 1954). Although each country's path to industrialisation reflected its unique structural and historical conditions, both early industrialisers (e.g., Great Britain, France, Belgium) and latecomers (e.g., Germany, Russia, Japan) ultimately reached high-income standards through a manufacturing-led growth strategy (Gerschenkron, 1962; Pollard, 1990; Szirmai, 2012).

However, recent empirical evidence suggests that, in the post-Second World War era, many developing regions have increasingly diverged from these historical trajectories (M. Timmer et al., 2015). Specifically, services have often expanded ahead of a sustained industrial base, while manufacturing has declined at much lower income levels than in the past, thereby peaking at much lower shares of output and employment — a pattern now termed premature deindustrialisation (Palma, 2005; Dasgupta and Singh, 2007; Palma, 2014; Rodrik, 2016; Tregenna, 2016). Put differently, the conventional hump-shaped relationship between income per capita and manufacturing appears to have shifted downward and leftward over time, leading to projected decreases in industrial employment and value-added shares at earlier stages of development. While this time-dependent pattern may indicate that manufacturing is a more difficult path to growth than before (Szirmai and Verspagen, 2015), the absence of robust alternative convergence pathways underscores the need to closely monitor the evolving dynamics manufacturing historical properties[1] (Haraguchi, Cheng et al., 2017).

As such, this paper sets out to investigate the extent to which manufacturing exhibits labour productivity convergence by examining productivity dynamics within sub-sectors. Put differently, it examines whether there is still a negative partial relationship between the initial level of labour productivity and subsequent productivity growth.

[1]One might argue that a growth strategy primarily focused on improving the *fundamentals* (i.e., human capital, institutions, etc.) could be sufficient. However, most developing countries cannot afford to settle for the low growth rates characteristic of advanced economies, as they must rapidly close the technological gap to achieve convergence (Rodrik, 2016). Furthermore, the tertiary sector appears ill-suited to play this role. Most services exhibit low productivity growth, while those with higher productivity — such as ICT activities — tend to depend on a highly skilled labour force and are, therefore, unable to absorb the large pools of low-skilled workers prevalent in emerging economies (Athukorala and Sen, 2015).

The motivation for this question is threefold. First, if manufacturing, in the aggregate, happen to be no longer an engine of growth (or a more difficult route to growth), it is important to establish whether this pattern holds across all sub-sectors, or only in some of them. Second, while the premature deindustrialisation literature documents the decline of manufacturing shares at earlier levels of income per capita since the 1990s, this does not amount to asking whether manufacturing still displays the productivity-enhancing dynamics historically associated with its role as an engine of growth in the Kaldorian tradition. Third, if convergence is observed, this would still lend support to the view that reallocating factors of production towards the manufacturing sector may generate economy-wide gains, provided that such reallocation is directed towards the sub-sectors exhibiting the fastest convergence.

This paper draws on the literature on convergence, which, through the lens of the neoclassical growth model, typically posits that poorer countries tend to grow faster than richer ones and catch up under certain conditions (Solow, 1956). While the earliest studies on convergence focused on per capita income (Barro, 1991; Barro and Sala-i-Martin, 1992; Barro, 2015; Patel et al., 2021), subsequent work extended this framework to labour productivity, particularly in manufacturing (Abramovitz, 1986; Rodrik, 2013). Recent work has renewed interest in this topic, but mostly through country-specific studies (Klein, 2023; Rivadeneira, 2024; Feng et al., 2025). By contrast, Rodrik (2013) remains the last major attempt to draw worldwide conclusions about the convergence properties of manufacturing at the sub-sector level. This paper seeks to update and extend his analysis.

In his seminal paper, Rodrik (2013) shows that labour productivity in manufacturing displays a clear tendency towards convergence. Yet, his results relyed on a small sample ($N^{Max} = 3,848$), largely cross-sectional estimations, and on a noisy database[2] in which labour productivity measures were not deflated[3]. While this was arguably the best that could be done at the time, the contribution of this paper is threefold. To the best of our knowledge, this is the first paper to examine worldwide convergence patterns in manufacturing using a robust panel framework that allows for the analysis of both temporal and sectoral heterogeneity on such a scale. This allows the paper to provide new insights into the evolution of manufacturing's growth-enhancing properties across time, sub-sectors, and countries. This is made possible by the paper's reliance on a newly harmonised database — the STiM Database (Bekhti, 2025) — covering 175 countries, 12 manufacturing sub-sectors, and six decades (1963-2019). As discussed in the data section, this database results from the compilation of more than 10 data sources and careful harmonisation efforts. Second, the paper implements several complementary convergence tests and, notably, documents the evolution of σ-convergence over time and tests for the presence of convergence clubs using the latest techniques (Phillips and

[2]For further details regarding these inconsistencies, see Section 2, which discusses the surveys and representative censuses collected by the United Nations Industrial Development Organization (UNIDO). As explained there, although these data became freely available only in 2022, Rodrik (2013) appears to have had access to them prior to that date.

[3]See Rodrik (2013) for further details. The inclusion of country–sub-sector fixed effects is argued to capture price differences, thereby allowing the use of nominal labour productivity measures.

Sul, 2007). Third, this comprehensive approach allows the paper to reassess the role of manufacturing in today's developing countries and engage with the conclusion of the premature deindustrialisation litterature.

In a nutshell, our findings suggest that the β-convergence hypothesis holds for manufacturing. Moreover, when allowing the β parameter to vary across sub-periods, the results suggest that the speed of convergence increased after the 1990s, with particularly strong increases in the 1990s and the 2000s. While one might have expected this effect to be driven by a small subset of manufacturing sub-sectors, the evidence shows that the increase in convergence is widespread across sub-sectors, including those often considered more traditional or classified as low-tech industries. Additionally, when examining the dispersion of productivity levels within manufacturing activities, it appears that σ-convergence went hand in hand with β-convergence only during the last thirty years. The evidence further shows that the dispersion of productivity levels within manufacturing in 2019 was, on average, almost exactly the same as sixty years earlier. This reflects a short ten-year episode of adverse and uneven productivity dynamics (1983-1993), which was sufficient to generate such a marked increase in cross-sector dispersion that reversing it required almost three decades. Lastly, the convergence club analysis suggests that global convergence cannot be rejected, implying that all countries converge towards a common steady state within each technological group.

The rest of the paper is structured as follows. The next section describes the data, while Section 3 presents descriptive statistics that foreshadow the main empirical findings. Section 4 empirically assesses convergence patterns in manufacturing, while Section 5 checks the sensitivity of the estimates. Lastly, Section 6 investigates the presence of convergence clubs, while Sections 7 and 8 offer concluding remarks.

2 Data

To investigate labour productivity convergence within manufacturing, we require a dataset that provides detailed information on labour productivity at the manufacturing sub-sectoral level over an extended period and across a large set of countries. Both dimensions are crucial for our analysis. First, any structural change study requires data covering a long period of time, since changes in the composition of the production structure are a long-term process, even when focusing on changes happening within a single sector as in our case (manufacturing). Second, regarding country coverage, it is necessary to ensure that the estimated convergence process reflects the intrinsic properties of manufacturing rather than being driven by a small set of manufacturing laggards or leaders. As such, it requires a large representative sample of countries.

In the last two decades, substantial progress has been made in this respect, with major improvements in data collection and harmonisation procedures. The release of new datasets has generally followed three approaches. The first set of databases provides long-term disaggregated data but only for a limited set of countries (Horvát and Webb, 2020; Woltjer et al., 2021; Nomura, 2025). The second provides disaggregated data for a larger set of countries but over a limited time span (Horvát, Webb and Yamano, 2020; Bontadini et al., 2023; OECD, 2025). Lastly, some databases shift the focus towards covering a larger set of countries over a longer period of time with complete sectoral coverage. Yet, this comes at the expense of a higher level of aggregation, making it impossible to study within-sector dynamics — and thus to obtain disaggregated data on manufacturing activities (M. Timmer et al., 2015; Kruse et al., 2022; Hamilton and Vries, 2025). As such, none of the existing datasets were suitable candidates, especially given that some of the aforementioned databases report either value added without employment data (or vice versa), making it impossible to estimate labour productivity measures.

To overcome these limitations, this paper draws on the new release of the Structural Transformation in Manufacturing (STiM) Database, which provides newly harmonised disaggregated data on manufacturing. The STiM database is the result of a comprehensive data compilation (12 sources) and harmonisation effort, making it the most comprehensive dataset for long-run analyses of structural change within manufacturing (Bekhti, 2025). While more details can be found in the accompanying paper, we provide in the next paragraphs a quick overview of how it has been constructed, its main features and limitations.

2.1 The construction of the STiM Database

The STiM database provides employment, value-added, and output data at the two-digit manufacturing level. It heavily relies on national industrial surveys and representative censuses collected by the United Nations Industrial Development Organization through its Industrial Statistics Database (INDSTAT). These data have been freely available since February 2022 and constitute the baseline for all final series, given their extensive country and temporal coverage (UNIDO, 2024). They follow the ISIC Rev. 3.1 classification as shown in Table 1. However, since these data come directly from national statistical offices, no systematic cleaning or harmonisation is officially performed by UNIDO, making them extremely noisy and unreliable without thorough preprocessing. In addition to unrealistic outliers, problematic exchange rates, spurious zeros, and duplicates observed over time, three major threats arise. First, the composition of manufacturing sub-sectors is not homogeneous over time, as several combinations of industrial activities are reported — these codes varying across countries, years, and even the variable considered (employment, value-added, etc.). While some combinations are simply the result of changes in the ISIC classification since the

1960s[4], most combination codes are the result of unusual reporting practices[5] across countries. In its raw form, the database reports 134 different possible combinations of activities.

Table 1: ISIC Rev. 3.1 Manufacturing Categories (Section D)

ISIC, Rev. 3.1	Initial ISIC Categories available
15	Food and beverages
16	Tobacco products
17	Textiles
18	Wearing apparel, fur
19	Leather, leather products and footwear
20	Wood products (excl. furniture)
21	Paper and paper products
22	Printing and publishing
23	Coke, refined petroleum products, nuclear fuel
24	Chemicals and chemical products
25	Rubber and plastics products
26	Non-metallic mineral products
27	Basic metals
28	Fabricated metal products
29	Machinery and equipment n.e.c.
30	Office, accounting and computing machinery
31	Electrical machinery and apparatus
32	Radio, television and communication equipment
33	Medical, precision and optical instruments
34	Motor vehicles, trailers, semi-trailers
35	Other transport equipment
36	Furniture; manufacturing n.e.c.
37	Recycling

The second main threat is the changes in reporting methods over time which reflect changes in the System of National Accounts (SNA) recommendations, which have evolved over time (United Nations, 1968b; International Monetary Fund, 2025). Yet, these changes are specific to each country and year, with absolutely no common pattern over time or across regions, as national statistical offices may or may not apply these rules. As such, employment can be reported as the number of employees or the number of persons engaged, while value-added and output can be reported under basic price,

[4]For instance, manufacturing activities linked to leather products and the footwear industry were only distinguished from the wearing apparel industry in the early 1990s. This became possible only with the introduction of the ISIC Rev. 3 classification in 1989 (United Nations, 1989). Consequently, there are no historical data for these activities prior to this date since national statistical institutes were all following the ISIC Rev. 2 classification then in force (United Nations, 1968a).

[5]One reason behind these practices is the need to avoid disclosing confidential information when a manufacturing activity is considered too small relative to statistical disclosure thresholds. In such cases, statistical offices report this given sub-sector jointly with another one to maintain confidentiality.

producer prices, factor cost or unknown valuation methods[6]. These changes, when they occur, introduce unintended variations, notably level shifts in time series.

To give a concrete example that also illustrates the first issue discussed earlier, consider the case of Peru. Peru correctly reports employment as the number of persons engaged in the Food and Beverages sector (ISIC 15, Rev. 3.1) without any combination from 1979 (the year of its entry into the database) to 2003. However, from 2004 to 2013 the country reports the Food and Beverages sector (ISIC 15, Rev. 3.1) combined with Tobacco products (ISIC 16, Rev. 3.1), before reverting to the original classification from 2014 to 2019. In addition, in 2014, Peru began reporting employment as the number of employees rather than as the number of persons engaged, thereby introducing additional noise and artificial variation into the series. This example is far from being an isolated case, as most countries in the database changes at least once their reporting methods and/or the composition of manufacturing sub-sectors.

Lastly, the third issue relates to the unbalanced nature of the industrial surveys, as series may start and end in different years across countries and contain several missing data across sub-sectors. While this is a common issue when dealing with long-term databases, the objective from the outset when constructing the STiM database was to ensure that it could fully exploit the major updates and new vintages of datasets released over the last two decades. The challenge in doing so is that most new databases providing data at the manufacturing sub-sectoral level are now available under the ISIC Rev. 4 classification rather than ISIC Rev. 3.1, which serves as the baseline classification for the long-term census data collected by UNIDO. Given that a perfect correspondence between the two classifications is impossible at the two-digit level, and that the census data themselves contain several combinations of activities, this further complicates the process of linking datasets across sources and time.

To mitigate these three main issues, the strategy adopted to build the STiM database was first to re-aggregate the data to ensure consistency across sub-sectors and to eliminate most combinations of activities in the baseline censuses. When doing so, we have also ensured that the new classification would also minimise misaligned sub-sectors across different ISIC revisions. This leads to the aggregation of the data into 12 manufacturing sub-sectors, as shown in Table 2. While moving from 23 sub-sectors in the ISIC Rev. 3.1 classification to 12 sub-sectors in the STiM classification may seem like a significant loss of information, this approach is the most effective way to ensure that times series are consistent across countries and over time, while remaining compatible with other

[6]In a nutshell, employment expressed as the number of persons engaged includes both salaried workers and the self-employed, while employment measured as the number of employees refers only to salaried workers. Under basic price valuation, subsidies on products are included while taxes are excluded to reflect what the producer actually receives (International Monetary Fund, 2025, p.214). Conversely, under producers' prices, taxes are included and subsidies excluded to assess what the producer charges (International Monetary Fund, 2025, p.214). Lastly, under factor cost, both taxes and subsidies on products are excluded, and value added is obtained by adjusting value added at basic prices for other taxes and subsidies on production (International Monetary Fund, 2025, p.218). Given that taxes and, notably, subsidies are well-known instruments of industrial policy (Aiginger and Rodrik, 2020), these different valuations methods can indeed lead to discrepancies.

major databases. The concordance table is provided in the accompanying paper and in Appendix A1.

Table 2: The 12 manufacturing sub-sectors included in the STiM Database

STiM	**Manufacturing sub-sector label**	**Techno. class.**
1	Food, beverages and tobacco products	Low-tech industries
2	Textiles, wearing apparel, leather products, fur	Low-tech industries
3	Wood products (excl. furniture)	Low-tech industries
4	Paper products, printing and publishing	Low-tech industries
5	Coke, refined petroleum products, nuclear fuel	Med-tech industries
6	Chemicals and chemical products	High-tech industries
7	Rubber and plastics products	Med-tech industries
8	Non-metallic mineral products	Med-tech industries
9	Basic and fabricated metal products	Med-tech industries
10	Machinery, equipment and electronic products	High-tech industries
11	Transport equipment	High-tech industries
12	Other manufacturing and recycling	High-tech industries

Note: The correspondence between each sub-sector and its technological intensity is derived from OECD (2003) and adapted following Vu et al. (2021). The STiM code number 12 — Other manufacturing and recycling — can be classified as either medium-tech or high-tech industries, since the sub-sectors it aggregates are typically assigned to both categories. To balance the classification (with four sub-sectors in each technological category), we assign it to high-tech industries. The concordance table between the STiM classification and major industrial classifications (ISIC Rev. 3.1, ISIC Rev. 3, ISIC Rev. 4 and NACE 2) can be found in the Appendix A1.

The second step involves the harmonisation of reporting methods in censuses and surveys (INDSTAT) and their linkage to other major databases. This is achieved by applying standard techniques such as chain-linking and splicing, which are commonly used in national accounts to ensure consistency across time and sources (Pahl and M. P. Timmer, 2020; De Vries et al., 2021). In short, we begin by establishing an initial cross-section of employment and value added for each country — the reference year. When possible, monetary variables expressed at basic prices are preferred over producer prices, then factor cost, and finally unknown classifications (in this order), while employment measured as the number of employees is prioritised over the number of persons engaged. This prioritisation follows the recommendations of the System of National Accounts (International Monetary Fund, 2009; International Monetary Fund, 2025).

From this baseline, raw data are then extrapolated backwards and forwards using combined growth-rate series[7]. These growth-rate series are constructed by prioritising rates stemming from INDSTAT and then from external datasets, provided that they follow the same preferred valuation methods scheme. Tables A2 and A3 in the Appendix provide a detailed overview of the different sources used to construct the final series and the priority order applied when computing these combined growth-rate series.

[7]The baseline is always internal to the census, i.e. derived from INDSTAT. We also apply careful interpolation limited to gaps of up to five years. As shown in the robustness section, the results remain robust when these observations are excluded.

In total, 12 external sources are compiled, allowing us to maximise both the coverage and the reliability of the estimates. Additionally, when two growth-rate segments for a country are available but separated by a break, we adopt two assumptions to fill the gap. Either labour productivity is assumed to remain constant or the missing growth rate of the sub-sector is assumed to follow the growth rate of total manufacturing in this year. These assumptions are standard in the literature and are applied only in a few cases[8]. Moreover, all these observations are explicitly flagged in the database to ensure transparency and facilitate robustness checks. Overall, this makes final STiM series consistent with SNA recommendations as the harmonisation procedure maximises internal, intertemporal, and international consistency.

At this stage, value-added and output series are expressed in nominal terms and in local currency units (LCU). To ensure meaningful productivity comparisons, we first use sub-sectoral deflators derived from INDSTAT (Haraguchi and Amann, 2023) and, when unavailable, rely on a harmonised GDP deflator (Müller et al., 2025) to deflate the series. While we acknowledge the limitations of the single-deflation approach and the partial reliance on GDP deflators, this remains the only viable option given the lack of sub-sectoral deflators for a large set of countries and years[9]. Finally, all value-added series are converted into constant 2015 US dollars using the Penn World Table (Feenstra et al., 2015), following the World Bank methodology designed to ensure that the real growth rates of the local economy are preserved.

2.2 Final sample and limitations

The final sample used in the analysis comprises 175 countries over the period 1963-2019, with labour productivity measured as real value-added per employee expressed in constant 2015 US dollars. It covers a wide range of economies, from low- to high-income countries, over nearly sixty years and allows distinguishing for 12 manufacturing sub-sectors. The list of countries covered is provided in the Appendix, in Table A4.

Despite several careful checks and harmonisation efforts, the STiM database is not free from limitations. In particular, it should be noted that the baseline of the dataset is derived from industrial surveys that traditionally exclude firms with fewer than five — and sometimes ten — employees, depending on the census. As a result, the database primarily captures formal and registered manufacturing activities, which represents the trade-off for obtaining consistent sub-sectoral data across a wide range of countries over a long period. This limitation thus applies to the rest of this paper.

[8] For example, Pahl and M. P. Timmer (2020) and De Vries et al. (2021) adopt a similar approach. Additionally, the constant labour productivity assumption is never imposed for more than three consecutive years and is used only when no alternative is available to bridge two growth-rate segments. As shown in the robustness section, the results remain robust when these observations are excluded.

[9] Kruse et al. (2022) rely on the method proposed by Schreyer (2002) to deflate nominal values. However, this approach is not suitable for our purposes, as exchange rates prior to the 1980s were often state-determined rather than market-based.

3 Descriptive statistics

To motivate the analysis, we first present some graphical visualisation regarding the productivity gap in manufacturing and some preliminary evidence regarding the presence of convergence across different technological groups.

3.1 Manufacturing productivity gaps across countries

We first provide a descriptive view of productivity gaps within manufacturing. To do so, we plot the average level of labour productivity of three technological groups of manufacturing sub-sectors against the average level of GDP per worker for the same country — a proxy for economy-wide labour productivity[10]. Both measures are normalised by the corresponding level in the United States, which serves as a proxy for the technological frontier. We end-up constructing the x-axis as follows:

$$\begin{aligned} x_{i,T} &= \frac{GDPpW^{agg}_{i,T}}{GDPpW^{agg}_{US,T}}, \\ \text{where} \quad GDPpW^{agg}_{i,T} &= \frac{1}{|T|}\sum_{t\in T} GDPpW^{agg}_{i,t}, \\ \text{and} \quad GDPpW^{agg}_{US,T} &= \frac{1}{|T|}\sum_{t\in T} GDPpW^{agg}_{US,t}. \end{aligned} \tag{1}$$

While the y-axis is constructed as follows:

$$\begin{aligned} y_{i,g,T} &= \frac{LP^{man}_{i,g,T}}{LP^{man}_{US,g,T}}, \\ \text{where} \quad LP^{man}_{i,g,T} &= \frac{1}{|T|}\sum_{t\in T}\left(\frac{1}{|g|}\sum_{j\in g} LP_{i,j,t}\right), \\ \text{and} \quad LP^{man}_{US,g,T} &= \frac{1}{|T|}\sum_{t\in T}\left(\frac{1}{|g|}\sum_{j\in g} LP_{US,j,t}\right). \end{aligned} \tag{2}$$

With i denoting the country, j the manufacturing sub-sector, g the technological group (i.e., Table 2), and T the period. For the purpose of the analysis, the graphs are constructed for three periods, namely 1963-1979, 1980-1999, and 2000-2019. While the choice of these periods is somewhat arbitrary, it divides the sample into intervals of roughly the same length and broadly corresponds to the usual temporal divisions used in cliometric analyses (M. S. McMillan and Rodrik, 2011; Forero and Tena-Junguito, 2024). The first period corresponds to the post-war decades, characterised by active industrialisation policies and sustained growth. The second one covers the shift in the global economic paradigm and the intensification of globalisation. It also captures the so-called *lost decades* of the 1980s and the subsequent recovery experienced by many developing countries. Finally, the third period captures the significant growth accelera-

[10] Data to compute real GDP per workers (i.e., the labour force) comes from the Penn World Tables (Feenstra et al., 2015).

tions in many developing economies from the last two decades, partly fuelled by the commodity price boom (Diao, M. McMillan et al., 2019). Comparing these three periods should be quite informative, as different dynamics may have shaped manufacturing performance across them.

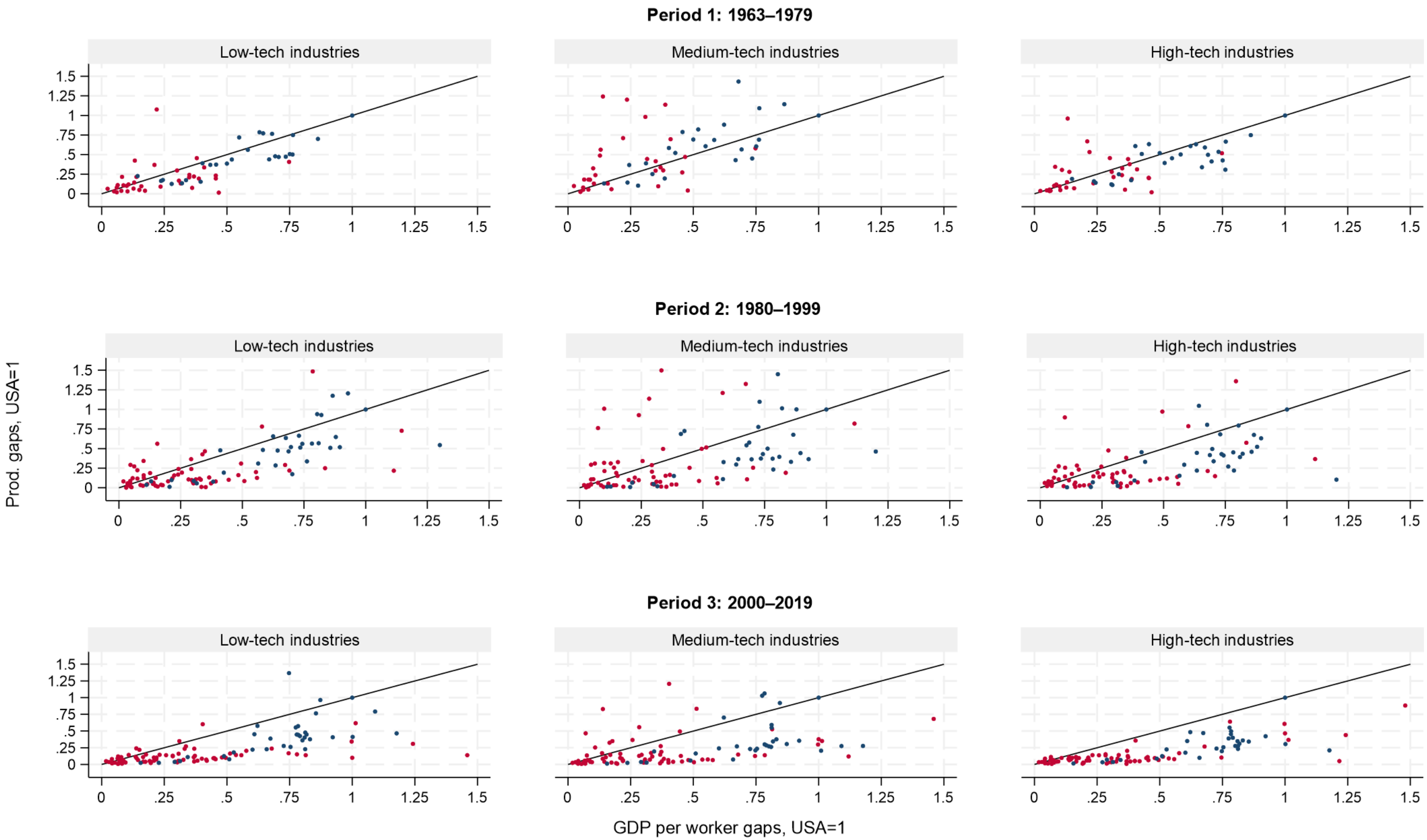
We present these descriptive evidence in Figure 1. For each period, three graphs are reported side-by-side, one for each technological group. For ease of interpretation, a solid line is plotted in each graph, which corresponds to the 45-degree line ($x = y$). Any observation on this line indicates that the productivity gap in the corresponding technological group is equal to the country's overall economy-wide productivity gap relative to the technological frontier represented by the United States. Said differently, it means that the group of manufacturing activities is as productive as the country's level of development suggests. As such, observations above (below) this line indicate that the productivity gap in the corresponding technological group is smaller (larger) than the country's overall economy-wide productivity gap, thereby implying that the corresponding technological group performs relatively better (worse) than the overall economy[11]. Colours of the markers are used to distinguish between developing[12] (red) and advanced economies (blue) as we might expect different patterns among them.

Two points are worth noting from these graphs. First, most developed economies are located around the 45-degree line, suggesting that their manufacturing productivity gaps are broadly in line with their overall economy-wide productivity gaps. Yet, the dispersion of observations below the 45-degree line becomes more pronounced in the later periods, suggesting that manufacturing productivity increasingly tends to lag behind overall economy-wide productivity relative to the United States. This relative decoupling appears particularly pronounced in the last two decades, and a quick eyeball suggests that it affects all technological groups. Second, most developing countries are located well below the 45-degree line, suggesting that their manufacturing productivity gaps are substantially larger than their overall economy-wide productivity gaps relative to the United States. While mid-tech activities seem to perform relatively better in this regard, the divergence nonetheless appears to have become particularly pronounced over the last four decades. A striking feature is that no observations for developing countries are located above the 45-degree line in the last two decades, when examining both low-tech and high-tech activities. This suggests that manufacturing activities in developing countries tend to perform significantly worse than the overall economy-wide productivity.

[11]For visual clarity, we exclude the small number of observations for which either the relative GDP per worker or the relative manufacturing productivity exceeds 1.5 (relative to the United States). These correspond to a handful of observations with exceptionally high aggregate productivity levels (from PWT) that would otherwise compress the scale of the figure.

[12]Countries are classified as developing or advanced using a simplified rule whereby all countries located in Europe, North America (excluding Mexico), and Advanced Asia (following the IMF classification) are considered advanced economies. All remaining countries are classified as developing economies. We acknowledge that this classification is simplistic, particularly given the substantial changes in income levels that have occurred over the last sixty years.

Figure 1: Manufacturing productivity gaps by technological intensity



Notes: Red markers denote developing economies, while blue markers denote advanced economies. For more details, refer to Equations 1 and 2. The solid line represents the 45-degree line. Any point on this line indicates that the productivity gap in the corresponding technological group is proportional to the country's overall economy-wide productivity gap relative to the technological frontier represented by the United States.

3.2 Labour productivity convergence in manufacturing

While Figure 1 suggests that manufacturing productivity in many developing countries remains substantially below what their overall level of development would predict, this static picture does not necessarily rule out the presence of convergence forces within manufacturing. To examine whether manufacturing sectors with lower initial levels of labour productivity experience faster subsequent productivity growth, we plot the average annual growth rate of labour productivity in manufacturing against its initial level for the same three periods as in the previous figure. Although the choice of periods remains somewhat arbitrary, it nonetheless provides a first visual illustration of the potential convergence effect over different time horizons. Since each dot now corresponds to a country–subsector pair, we also estimate separate fitted lines for each technological group of manufacturing activities. This allows us to visually assess whether the speed of convergence (if any) differs across types of manufacturing activities.

The three graphs are reported side-by-side in Figure 2. While these are simple static visualisations, they tend to provide strong support for the presence of convergence in manufacturing productivity across all three periods. The fitted lines for the three technological groups display a clear negative slope in each period, suggesting that sub-sectors with lower initial productivity tend to experience faster subsequent growth, while those with higher initial productivity grow more slowly. A visual comparison across the three periods also suggests that convergence was slowest during the 1980-1999 period and stronger during the most recent decades. Lastly, the fitted lines for high-tech manufacturing appear somewhat steeper than those for low- and medium-tech manufacturing, which may suggest a slightly faster convergence pattern for these activities. These patterns are further investigated in the next section using more formal methods.

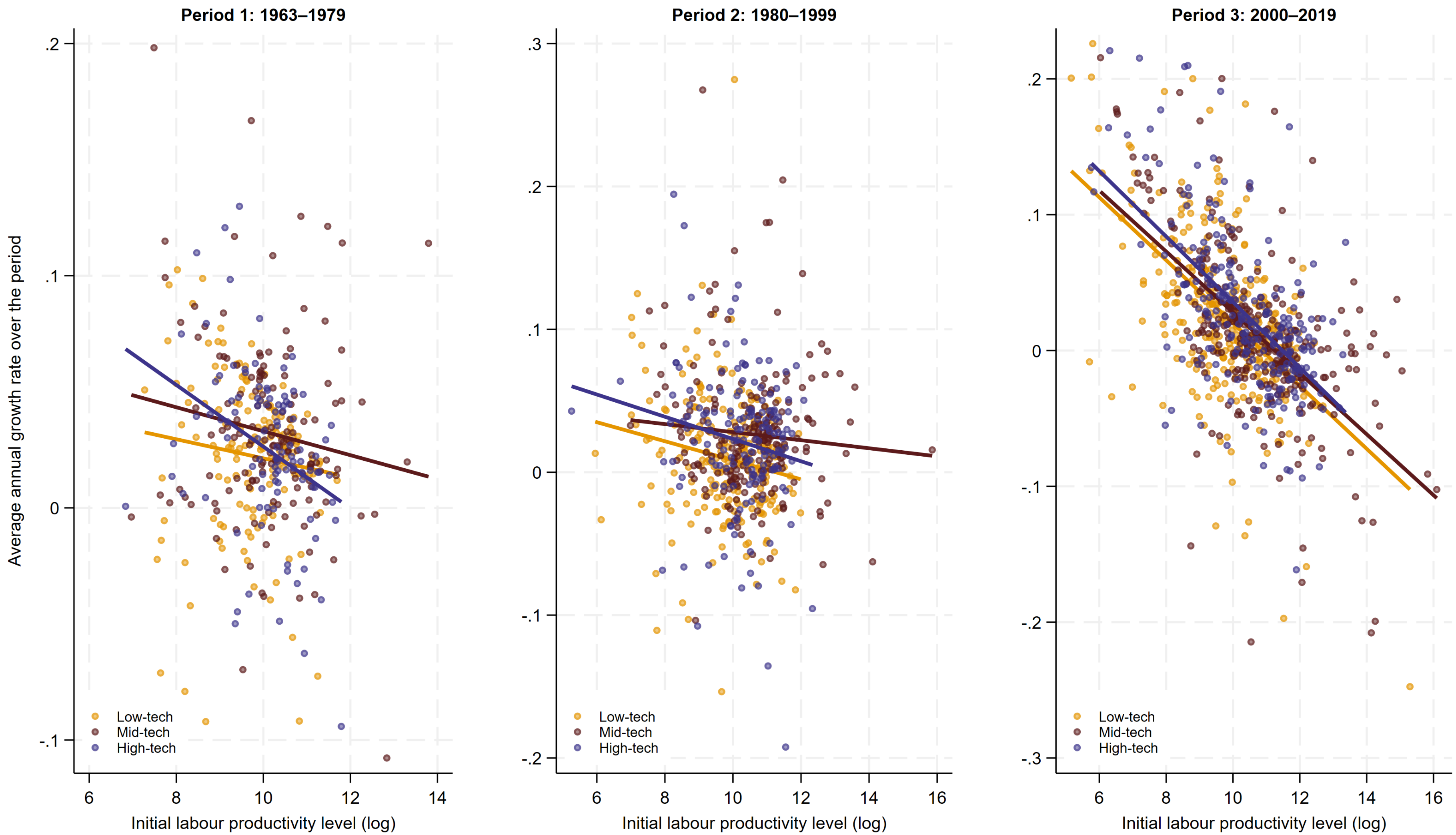
4 Convergence tests

This section presents an empirical assessment of convergence patterns in labour productivity across manufacturing sub-sectors and countries over the period 1963-2019. We rely on two complementary frameworks to discuss these dynamics, namely β-convergence and σ-convergence.

4.1 The beta convergence framework

We begin the analysis by examining whether the β convergence framework applies to labour productivity in manufacturing. This approach consists of assessing whether less productive manufacturing sub-sectors are narrowing (or broadening) their gap with more productive ones as time goes on. As implied by neoclassical growth theories, manufacturing sub-sectors that are further from the technological frontier are

Figure 2: Is there convergence in manufacturing labour productivity?



Notes: Each dot represents a country-subsector pair. The solid line represents the fitted line for each technological group of manufacturing activities. The slope of this line provides a visual indication of the presence and speed of convergence within manufacturing. A negative slope suggests that sub-sectors with lower initial productivity tend to experience faster subsequent growth, while those with higher initial productivity grow more slowly.

expected to experience faster labour productivity growth than the closest ones, thereby generating convergence dynamics. In other words, manufacturing sub-sectors with lower initial levels of labour productivity should exhibit higher labour productivity growth rates in the subsequent years than their more productive counterparts. We test this hypothesis relying on the following standard econometric specification:

$$(\ln y^{LP}_{ij,T} - \ln y^{LP}_{ij,t_0})/T = \alpha + \beta \cdot \ln y^{LP}_{ij,t_0} + D_i + D_{j\times t} + \varepsilon_{ijt} \tag{3}$$

Where the dependent variable corresponds to the average annual growth rate in labour productivity y of manufacturing sub-sector j in country i over a finite period of T years. The growth rate is then regressed on the logged initial level of labour productivity at the beginning of the period ($\ln y^{LP}_{ij,t_0}$), along with a set of fixed effects D. Specifically, we include country, sub-sector, and year fixed effects, as well as sub-sector-by-year fixed effects. This unbalanced panel structure allows controlling for all time-invariant country and sub-sector characteristics, common global shocks, as well as sector-specific shocks in a given year. In this setting, the β parameter is thus estimated using cross-country variation in labour productivity within the same manufacturing sub-sector and year.

Note that when including some country fixed effects, Equation 3 tests for conditional β-convergence, as the speed of convergence is conditional on country-specific structural characteristics. Conversely, excluding country dummies from the specification proxies unconditional β-convergence according to which labour productivity converge to one another in the long-run independently of their initial conditions, that is, differences are transitory. We estimate both versions for comprehensiveness using pooled OLS, with standard errors clustered at the country-manufacturing sub-sector level. Lastly, in all the results discussed in this section, we report estimates based on the annual growth rate (i.e., $T = 1$). However, we also estimate the same specifications using $T = 3$, $T = 5$ and $T = 10$ to assess the robustness of the findings (see the robustness section for further details).

Specifications 1 and 6 from Table 3 report point estimates for the whole sample and the full period. The negative and statistically significant β coefficient strongly supports the presence of both unconditional and conditional β-convergence, highlighting a negative partial correlation between labour productivity growth and its initial level. In the unconditional convergence scenario, a 1% increase in the initial level of labour productivity is associated with a 0.052 percentage point decrease in the average annual growth rate of labour productivity. To provide an intuitive illustration of the implied speed of convergence, consider labour productivity in the vehicle and transport equipment sector in 1980 in Pakistan (USD \$12,780) and in the United States (USD \$94,687). Based on the estimated coefficient (β) and the constant (α), the predicted average annual growth rate for this sector would be approximately 7 percent in Pakistan. Holding all else constant, this implies that it would take around 29 years (by 2009) for Pakistan to catch up with the U.S. initial level of labour productivity in this sector. This points toward a relatively slow process of unconditional convergence, especially considering that by 2009 U.S. labour productivity in this sector had increased to USD $170,611 per worker.

Under conditional convergence, the estimated coefficient is slightly more than twice as large in absolute value, reaching -0.121 p.p, which implies a considerably faster convergence process. Said differently, a 1% increase in the initial level of labour productivity is associated with a 0.121 percentage point decrease in the average annual growth rate of labour productivity. It suggests that country-specific structural characteristics play an important role in shaping catch-up dynamics and accelerating convergence. This is in line with the literature discussing both per capita income convergence or the one investigating productivity convergence which highlight the importance of some factors such as institutions, geography or human capital in shaping these dynamics (Rodrik, 2013; Klein, 2023; Rivadeneira, 2024). Nevertheless, there are strong reasons to believe that these average estimates may conceal substantial heterogeneity in convergence patterns across time periods and manufacturing activities. We therefore extend the baseline model along these two dimensions to explore heterogeneous patterns of conditional and unconditional convergence.

4.1.1 Heterogeneity in convergence over different time periods

As discussed in the introduction, the ability of manufacturing to remain an engine of growth for developing countries has been significantly challenged in recent decades (Chang and Andreoni, 2020). Part of the recent discussions has revolved around the shift of the turning point towards lower income levels in the classic hump-shaped relationship between manufacturing employment and per capita income after the 1990s, suggesting a more difficult route to growth than before (Palma, 2005; Tregenna, 2016; Rodrik, 2016). Although this descriptive evidence does not necessarily imply a weakening of the historical properties associated with industrialization, some have argued that manufacturing has lost its role as an engine of growth based on that. As such, the corresponding testable hypothesis is that the speed of convergence may have evolved over time.

To explore this aspect, we estimate two augmented versions of the baseline model that allow the convergence parameter to vary across different time periods. The first specification separates the convergence estimates into pre- and post-1990 periods to mirror the conventional divide used when investigating premature deindustrialisation scenarios (Kruse et al., 2022). The second specification goes further by dividing the overall effect by decades, taking advantage of the extensive temporal coverage of the STiM database. A test equation for labour productivity convergence in this setting is:

$$(\ln y^{LP}_{ij,T} - \ln y^{LP}_{ij,t_0})/T = \alpha + \beta_1 \cdot \ln y^{LP}_{ij,t_0} + \beta_2 \cdot \ln y^{LP}_{ij,t_0} \times Post90_t + D_i + D_{j\times t} + \varepsilon_{ij,t} \quad (4)$$

Where the dependent variable is the same as in Equation 3, i.e., the average annual growth rate of labour productivity in manufacturing. Like in a difference-in-differences approach, the interaction between the initial level of labour productivity and the set of time dummies (minus their respective benchmark) allows testing for differences in the convergence parameter across different time periods. In the first specification, $Post90_t$ corresponds to a dummy capturing years greater than or equal to 1990, with pre-1990 years serving as the baseline. Hence, the marginal effect of initial labour productivity on subsequent growth in the post-1990s period is given by the sum $\beta_1 + \beta_2$.

$$(\ln y^{LP}_{ij,T} - \ln y^{LP}_{ij,t_0})/T = \alpha + \beta \cdot \ln y^{LP}_{ij,t_0} + \sum_{\substack{d=1 \\ d\neq 1}}^{6} \lambda_d \cdot \left(\ln y^{LP}_{ij,t_0} \times P^d_t \right) + D_i + D_{j\times t} + \varepsilon_{ij,t} \quad (5)$$

In the second specification (i.e. Equation 5), the set of time dummies P^d_t corresponds to decade dummies ranging from the 1960s to the 2010s, where $d = 1$ for the 1960s, $d = 2$ for the 1970s, and so forth. This results in the inclusion of six interaction terms, with the interaction corresponding to the 1960s being omitted and therefore serving as the reference category. Accordingly, the coefficient β captures the effect of initial labour productivity on subsequent growth in the 1960s, while the coefficients λ_d measure decade-specific deviations from this baseline effect. In this setting, the marginal effect of initial labour productivity on subsequent growth in decade d is therefore given by the sum $\beta + \lambda_d$. We estimate the two models with pooled OLS and the same set of fixed effect as in Equation 3, clustering standard errors at the country-manufacturing sub-sector level. For comprehensiveness, we also estimate Equation 4 and 5 with and without country fixed effects (D_i) to capture conditional and unconditional convergence, respectively.

Results are shown in Table 3 alongside the main coefficients for the whole sample. Both the unconditional and conditional convergence scenarios go in the same direction and suggest that the speed of convergence has increased over time, particularly in the post-1990s period. In the unconditional convergence setting, column 2 suggests that, relative to the pre-1990s period, the speed of β-convergence in the later years is multiplied by 2.6 (from -0.024 p.p. to -0.064 p.p. when computing the marginal effect). A more modest yet still significant increase is found in the conditional convergence scenario in column 7, with a multiplication factor of 1.3, leading to a specific β-convergence of -0.129 p.p. in the post-1990s period.

The decade-specific estimates in columns 3 and 8 confirm this pattern and further suggest that the increase in the speed of convergence is particularly strong in the 1990s and the 2000s relative to the 1960s. In the 1990s, a 1% higher initial labour productivity is associated with a 0.076 and 0.051 percentage-point lower average growth rate in the unconditional and conditional specifications, respectively, relative to the 1960s, the omitted baseline. In both cases, the 1990s, followed by the 2000s, are the decades with the highest speed of convergence in the last sixty years. This finding suggests that countries that successfully expanded their manufacturing shares during these two decades may have benefited from substantial payoffs in terms of economy-wide productivity growth, provided that other aggregate sectors (services, agriculture, etc.) did not perform comparatively worse. In a nutshell, if any change in the speed of convergence occurred over time, the results presented here (and the robustness checks below) indicate an increase rather than a decrease, with an effect that tends to be particularly strong in the 1990s and the 2000s, irrespective of the inclusion of country fixed effects.

4.1.2 Heterogeneity in convergence across manufacturing sub-sectors

Since long-standing contributions in the literature, there are reasons to believe that convergence processes may differ across manufacturing industries due to their specific characteristics (Hirschman, 1958; Hirschman, 1968; Szirmai, 2012). In this regard, one may expect some manufacturing activities to converge faster towards high productivity levels than others because of their higher R&D intensity, higher human capital content, or greater exposure to international trade. We explore this heterogeneity in two ways hereafter. First, we allow the convergence coefficient to vary across three technological groups encompassing different manufacturing sub-sectors — low-tech, mid-tech, and high-tech. We do so by relying on the classification from OECD (2003) and recently adjusted in Vu et al. (2021). More details on the classification of manufacturing sub-sectors into these three groups are provided in the data section. Second, we estimate separate convergence equations for each of the twelve manufacturing sub-sectors to directly compare the speed of convergence across them. This is implemented as follows:

$$(\ln y^{LP}_{ij,T} - \ln y^{LP}_{ij,t_0})/T = \alpha + \beta \cdot \ln y^{LP}_{ij,t_0} + \sum_{\substack{g=1 \\ g\neq 1}}^{3} \delta_g \cdot \left(\ln y^{LP}_{ij,t_0} \times G^g_j \right) + D_i + D_{j\times t} + \varepsilon_{ijt} \quad (6)$$

As in previous specifications, we rely on simple interaction terms between the initial level of labour productivity and a set of technological group dummies G^g_j. In this setting, $g = 1$ stands for low-tech manufacturing sub-sectors, while $g = 2$ and $g = 3$ denotes mid-tech and high-tech ones, respectively. The low-tech group is omitted and therefore serves as the baseline category. Accordingly, the coefficient β captures the effect of initial labour productivity on subsequent growth in low-tech manufacturing sub-sectors, while the remaining coefficients δ_g measure group-specific deviations from this baseline effect. As such, the marginal effect of initial labour productivity on subsequent growth within technological group g is given by the sum $\beta + \delta_g$. We estimate Equation 6 in the exact same setting as previous models.

In the unconditional setting, mid-tech and high-tech activities indeed appear to exhibit greater convergence speeds than low-tech ones. That said, when excluding the aforementioned sub-sector number five from the analysis, the mid-tech interaction with the initial level of labour productivity no longer differs significantly from the low-tech baseline, while the high-tech interaction remains significant (at the 10% level). This suggests a faster convergence process within this group, given that a 1% higher initial level of labour productivity in high-tech sub-sectors is associated with a 0.012 percentage-point lower average annual growth rate relative to low-tech sub-sectors. In the conditional convergence setting, the decomposition across technological groups does not yield significant differences relative to low-tech sub-sectors, except when

Table 3: β-convergence estimates for labour productivity in manufacturing sub-sectors

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial value (L1)	-0.052***	-0.024***	-0.013***	-0.044***	-0.044***	-0.121***	-0.098***	-0.090***	-0.121***	-0.127***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
×Post-1990s		-0.040***					-0.031***			
		(0.004)					(0.004)			
×1970*s*			-0.007					-0.009*		
			(0.005)					(0.005)		
×1980*s*			-0.017***					-0.007		
			(0.006)					(0.005)		
×1990*s*			-0.076***					-0.051***		
			(0.007)					(0.006)		
×2000*s*			-0.042***					-0.031***		
			(0.006)					(0.006)		
×2010*s*			-0.027***					-0.025***		
			(0.007)					(0.008)		
×Mid-tech				-0.013**	-0.009				0.001	-0.012**
				(0.006)	(0.006)				(0.005)	(0.005)
×High-tech				-0.012*	-0.012*				-0.001	-0.000
				(0.006)	(0.006)				(0.006)	(0.006)
Constant	0.562***	0.539***	0.506***	0.561***	0.539***	1.256***	1.230***	1.199***	1.256***	1.339***
	(0.027)	(0.026)	(0.024)	(0.027)	(0.026)	(0.054)	(0.052)	(0.053)	(0.053)	(0.052)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	42,377	42,377	42,377	42,377	39,096	42,377	42,377	42,377	42,377	39,096
Adj-R2	0.070	0.074	0.078	0.070	0.071	0.118	0.120	0.121	0.118	0.129

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Robust standard errors clustered at the country–manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

excluding the oil, fuel, and gas extraction sub-sector. In this case, mid-tech sub-sectors exhibit a significantly faster convergence process than low-tech ones (-0.012), while high-tech sub-sectors display a convergence speed statistically undifferent from that of low-tech activities. Overall, results in both specifications suggest that the convergence process remains broadly stable across technological groups, with no group clearly driving or slowing the overall convergence process discussed above — at least not consistently across both scenarios.

To assess whether this pattern holds at a more disaggregated level and to examine whether this relative stability conceals heterogeneity across sub-sectors, we estimate separate convergence equations for each manufacturing sub-sector. We do so by interacting the initial level of labour productivity with each manufacturing sub-sector dummy D_j, where $j \in \{1, \ldots, 11\}$ corresponds to the sub-sectors listed in Table 2. Note that we exclude sub-sector number twelve (i.e., recycling and other manufacturing activities) from this empirical exercise due to insufficient observations in the pre-1990s period. This results in the inclusion of 11 interaction terms, with the interaction corresponding to the first sub-sector (i.e., food, beverages, and tobacco products) omitted and therefore serving as the reference category for the initial labour productivity coefficient. The test equation is as follows:

$$(\ln y_{ij,T}^{LP} - \ln y_{ij,t_0}^{LP})/T = \alpha + \beta \cdot \ln y_{ij,t_0}^{LP} + \sum_{\substack{j=1 \\ j \neq 1}}^{11} \phi_j \cdot \left(\ln y_{ij,t_0}^{LP} \times D_j \right) + D_i + D_{j \times t} + \varepsilon_{ijt} \quad (7)$$

For the purpose of the analysis, Equation 5 is estimated over three periods: the full sample, the pre-1990 period, and the post-1990 period. For each specification, we test both the conditional and unconditional settings. This exercise allows us to assess whether the relative convergence speed across sub-sectors has evolved over time and to ensure that the apparent stability across technological groups is not an artefact. While the specification otherwise remains unchanged, identifying sector-specific convergence effects requires excluding individual sub-sector fixed effects, making the estimates potentially sensitive to time-invariant sub-sector characteristics. Yet, since sector-by-year fixed effects are retained, identification still rely on within-sector, within-year variation across countries. We only report marginal effects from the estimation results — given by the sum $\beta + \phi_j$ — so that the total convergence effect for each sub-sector can be directly compared.

Marginal effects are reported in Table 4. To ease identification of the fastest convergence speeds across specifications, we highlight in bold the two sub-sectors exhibiting the highest convergence rates (i.e., the most negative marginal effects) in each column. In doing so, we exclude sub-sector number five from this visual inspection, even though it does not systematically display the highest point estimates. Overall, the main striking result is that nearly every manufacturing sub-sector exhibits a highly significant convergence process, regardless of the period considered or the type of convergence

Table 4: β-convergence marginal effects by manufacturing sub-sector

	Uncondtional convergence			Condtional convergence		
	(1) Overall	(2) Pre-90s	(3) Post-90s	(4) Overall	(5) Pre-90s	(6) Post-90s
Food, beverages and tobacco products	-0.042***	-0.014	-0.056***	-0.132***	-0.090***	-0.159***
	[-0.059,-0.025]	[-0.030,0.003]	[-0.075,-0.037]	[-0.148,-0.116]	[-0.108,-0.072]	[-0.178,-0.140]
Textiles, wearing apparel, leather, fur	-0.041***	-0.018***	-0.049***	-0.119***	-0.085***	-0.138***
	[-0.054,-0.028]	[-0.031,-0.005]	[-0.066,-0.033]	[-0.133,-0.104]	[-0.101,-0.069]	[-0.156,-0.120]
Wood products (excl. furniture)	-0.044***	-0.010**	-0.059***	-0.117***	-0.077***	-0.141***
	[-0.057,-0.031]	[-0.020,-0.001]	[-0.076,-0.043]	[-0.132,-0.103]	[-0.091,-0.064]	[-0.161,-0.120]
Paper products, printing and publishing	-0.051***	-0.019**	-0.067***	-0.138***	-0.093***	**-0.166***
	[-0.067,-0.035]	[-0.035,-0.004]	[-0.088,-0.047]	[-0.154,-0.122]	[-0.109,-0.077]	[-0.186,-0.145]
Coke, refined petroleum, nuclear fuel	-0.063***	-0.052***	-0.066***	-0.100***	-0.095***	-0.106***
	[-0.082,-0.044]	[-0.079,-0.025]	[-0.088,-0.044]	[-0.120,-0.080]	[-0.123,-0.067]	[-0.130,-0.082]
Chemicals and chemical products	-0.055***	-0.026***	-0.066***	-0.128***	**-0.102****	-0.142***
	[-0.074,-0.037]	[-0.045,-0.007]	[-0.089,-0.043]	[-0.146,-0.110]	[-0.120,-0.083]	[-0.163,-0.120]
Rubber and plastics products	-0.052***	-0.021**	-0.065***	**-0.140****	-0.101***	-0.164***
	[-0.069,-0.035]	[-0.037,-0.005]	[-0.087,-0.044]	[-0.157,-0.124]	[-0.117,-0.086]	[-0.187,-0.142]
Non-metallic minerals products	-0.045***	-0.015***	-0.060***	-0.127***	-0.090***	-0.151***
	[-0.059,-0.032]	[-0.026,-0.005]	[-0.079,-0.041]	[-0.142,-0.113]	[-0.104,-0.077]	[-0.171,-0.131]
Basic and fabricated metal products	**-0.066****	**-0.029****	**-0.081****	**-0.145****	**-0.106****	**-0.169****
	[-0.083,-0.048]	[-0.050,-0.008]	[-0.102,-0.061]	[-0.163,-0.128]	[-0.124,-0.088]	[-0.192,-0.146]
Machinery, equipments and electronics	-0.051***	-0.021*	-0.061***	-0.121***	-0.094***	-0.138***
	[-0.066,-0.035]	[-0.043,0.000]	[-0.080,-0.042]	[-0.136,-0.106]	[-0.113,-0.075]	[-0.156,-0.119]
Vehicles and other transports equipments	**-0.062****	**-0.033****	**-0.076****	-0.129***	-0.101***	-0.148***
	[-0.082,-0.043]	[-0.057,-0.009]	[-0.098,-0.054]	[-0.151,-0.107]	[-0.134,-0.069]	[-0.170,-0.126]
N	41820	14714	27106	41820	14714	27106

Notes: Marginal effects are computed as $\beta + \phi_j$ following Equation 7. Robust standard errors clustered at the country–manufacturing sub-sector level are not shown. Instead, we report confidence intervals in brackets to highlight that most point estimates overlap, indicating that all manufacturing sub-sectors exhibit convergence, although differences across them are not statistically significant. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

specification[13]. Put differently, every manufacturing sub-sector remain characterised by a dynamic *structural change bonus*, suggesting that the reallocation of resources towards manufacturing is always associated with faster aggregate productivity growth, regardless of the activity considered.

Looking at the point estimates, the convergence process appears to be particularly strong in basic and fabricated metal products in both the unconditional and conditional settings across all periods. This is the sub-sector with the highest convergence speed in all columns. The second sub-sector with the highest convergence speed in the unconditional specification is vehicles and transport equipment, again consistently across periods. In the conditional setting, the sub-sector with the second-highest convergence speed varies more across periods, with the largest point estimates observed in rubber and plastic products (full sample), chemicals and chemical products (pre-1990s), and paper, printing, and publishing (post-1990s). Yet, these conclusions regarding the most rapidly converging sub-sectors warrant caution, as confidence intervals typically overlap across sub-sectors as displayed in Table 4. This reinforces the view that the convergence process is not driven by any specific manufacturing activity but instead appears to be a common feature across all of them. Most importantly, in line with the evidence presented above, if any change has occurred over time, it reflects an increase in the speed of convergence across every manufacturing sub-sector, no matter the type of convergence considered.

4.1.3 A brief summary of the beta convergence results: the half-life estimates

As a matter of summary, one convenient way to interpret the estimated β-convergence coefficient is to compute the implied half-life of convergence, denoted $\mu_{1/2}$. The half-life corresponds to the time required for a manufacturing sub-sector to eliminate half of its initial gap relative to its steady-state (or technological frontier) level. This criterion is often used in the literature about income convergence, being implicitly derived from neoclassical growth models assumptions (Barro, 2015; Patel et al., 2021). In our setting, with $T = 1$, the half-life is computed as follows:

$$\mu_{1/2} = \frac{\ln(0.5)}{\ln(1+\beta)} \tag{8}$$

This simple transformation allows the conversion of the β-convergence coefficient into a more intuitive measure of the speed of convergence expressed in years, namely the amount of time it takes for half of the remaining productivity gap to disappear. For more details on the half-life, please refer to Barro (1991) and Barro and Sala-i-Martin (1992).

To make things straightforward, let us consider again the case of Pakistan and the U.S. in the vehicle and transport equipment sector in 1980. In the previous section, to provide an illustration of the overall unconditional coefficient estimated over the

[13] The only non-significant estimate among the 66 coefficients in Table 4 corresponds to the food and beverage sub-sector prior to the 1990s.

whole sample and period, we predicted the annual growth rate in Pakistan in this sector. We thus assumed that this rate would remain constant over the following years, while keeping the initial U.S. productivity level constant (fixed at its 1980 level). This simple illustration suggested that it would take around 29 years for Pakistan to catch up with the initial level of labour productivity observed in the U.S. in this sector. In the half-life framework, by contrast, convergence follows a geometric adjustment process in which the productivity gap shrinks proportionally to the remaining distance from the technological frontier. In other words, the closer an economy is to the frontier, the slower the convergence process becomes. In this case, the corresponding half-life estimate suggests that it would take around 13 years for Pakistan to eliminate half of its initial productivity gap on average. After 13 years, half of the initial gap would therefore remain such that after another 13 years, only one quarter of the initial gap would remain, and so on.

Table 5: Years it takes for half of the remaining productivity gap to disappear

	Uncond. Convergence			Condit. Convergence		
	(1)	(2)	(3)	(6)	(7)	(8)
Baseline (half-life)	13	29	53	5	7	7
Post-1990s (half-life)	–	10	–	–	5	–
1970s (half-life)	–	–	53	–	–	7
1980s (half-life)	–	–	23	–	–	7
1990s (half-life)	–	–	7	–	–	5
2000s (half-life)	–	–	12	–	–	5
2010s (half-life)	–	–	17	–	–	6

Note: Half-life estimates are computed based on the β-convergence coefficients reported in Table 3 using Equation 8. For each interaction term, we compute the marginal effect of initial labour productivity on subsequent growth during the relevant period by summing the baseline β and the corresponding interaction coefficient (either β_2 or λ_d). Accordingly, in specifications 2 and 7 the baseline half-life corresponds to the pre-1990 period (1963–1989), while in specifications 3 and 8 it corresponds to the 1960s period (1963–1969).

Half-life estimates are reported in Table 5 following β-convergence coefficients from Table 3. For the sake of clarity, we only report half-life estimates from the first three specifications of each convergence scenario, i.e., the baseline model and the two models allowing the parameter to vary across different time periods. We do not report half-life estimate for models in the cross-sectoral heterogeneity analysis, as the convergence speed is broadly similar across sub-sectors (except some small exceptions) and therefore does not yield meaningful differences in terms of half-life estimates, especially considering that confidence intervals typically overlap across sub-sectors. In the unconditional convergence setting, the baseline half-life estimate is around 13 years, which suggests a somewhat fast convergence process, especially when compared with the estimate reported by Rodrik (2013), whose coefficient (-0.018) implies a half-life of approximately 38 years. As in Rodrik (2013), the conditional specification leads to a much faster convergence process, with the estimated speed roughly doubling or even tripling, resulting in a half-life of around 5 years (overall sample). Lastly, as suggested by the previous estimates, the speed of convergence has increased over time, with the half-life dropping from around 29 years in the pre-1990s period to around 10 years in the post-1990s period in the unconditional setting, and from around 7 years to around 5 years in the conditional setting. This acceleration is particularly pronounced in the 1990s and the 2000s, with half-life estimates averaging roughly 9,5 years in these decades in the unconditional scenario ($(7+12)/2$) and 5 years in the conditional setting.

4.2 The sigma convergence framework

While the β-convergence framework provides useful insights, recent literature cautions against drawing conclusions solely from the sign of the estimated coefficient (Cuadrado-Roura et al., 1999; Young et al., 2008; Rodrik, 2013; Bhattarai and Qin, 2022). Indeed, β-convergence does not necessarily imply that the dispersion of productivity levels across economies decreases over time — the phenomenon commonly referred to as σ-convergence (Young et al., 2008). While poorer economies may grow faster on average, shocks and heterogeneous growth trajectories may lead to a decoupling between β-convergence and σ-convergence.[14] As such, the remaining part of this section is devoted to investigating whether σ-convergence has occurred hand-in-hand with β-convergence in the manufacturing sector or if, at any point in time, the two measures of convergence have diverged.

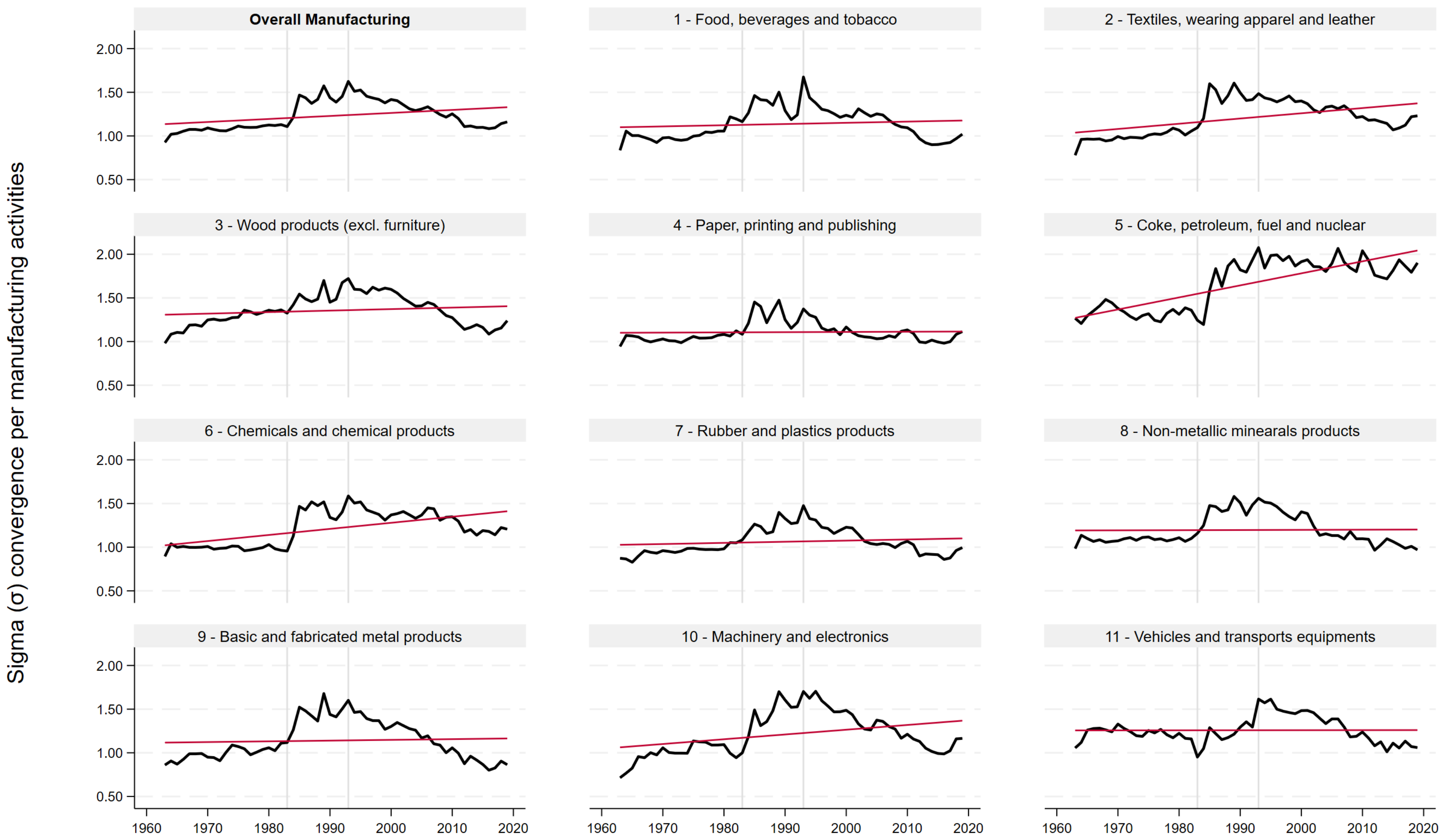
To examine whether productivity dispersion has declined over time, the usual (simple) approach is to analyse the standard deviation of the labour productivity. As shown in Equation 9, we thus compute the standard deviation of the log of labour productivity for each manufacturing sub-sector and years mixing countries. A declining trend in this measure over time would indicate that the dispersion of labour productivity across manufacturing sub-sectors is decreasing, while the opposite would support the absence of σ-convergence.

$$\sigma_{j,t} = \sqrt{\frac{1}{N_{j,t}} \sum_{i=1}^{N_{j,t}} \left(\ln LP_{i,j,t} - \overline{\ln LP}_{j,t} \right)^2} \tag{9}$$

The evolution of the standard deviation of the log of labour productivity over time is plotted in Figure 3. Before turning to the analysis, four points warrant discussion. First, for the sake of comparison, we also compute the average cross-country dispersion of labour productivity across manufacturing sub-sectors (computed as a simple mean of sector-specific standard deviations). It is reported in the top-left panel and is labelled as 'overall manufacturing'. Second, to ease the interpretation of the trends, we include a linear fitted line for each sub-sector. Third, we drop sub-sector number 12 (recycling and other manufacturing activities) due to insufficient observations prior to the 1990s. Lastly, we acknowledge that the σ-convergence analysis is mechanically affected by

[14] For the mathematical formalisation of this relationship, see Young et al. (2008).

Figure 3: σ-convergence across manufacturing sub-sectors



Notes: This figure plots the evolution of the standard deviation of the log of labour productivity across manufacturing sub-sectors from 1963 to 2019. It is based on the same sample as the β-convergence analysis, i.e., an unbalanced panel, simply omitting the sub-sector number 12 (recycling and other manufacturing activities) due to insufficient observations in the pre-1990s period. For the analysis without the sector number 5, refer to figure A1 and for the analysis using a perfectly balanced panel, refer to figure A2.

the unbalanced nature of the sample and the different time coverage across sub-sectors and countries. While Figure 3 relies on the same panel as the β-convergence analysis, we also provide two additional versions of this figure in the appendix: one excluding sub-sector number five (oil, fuel, and gas extraction), and another using a balanced panel including only countries with complete data throughout the whole period (see Figures A1 and A2). In both cases, the overall pattern remains unchanged. We therefore report the σ-convergence analysis based on the unbalanced panel as it is the one that maximizes the number of observations ($N = 39,096$).

Overall, the results suggest that, over the last sixty years, the dispersion of labour productivity levels across manufacturing has remained broadly stable as indicated by the fitted line in the top-left panel, i.e. the average dispersion of labour productivity in manufacturing. This stability is even more striking when excluding the oil, fuel, and gas extraction sub-sector, as shown in Figure A1. However, within this broad stability, three main periods can be easily identified. First, from 1963 to 1983, the dispersion of labour productivity across manufacturing sub-sectors remained quite stable, suggesting that the β-convergence process observed in the previous section was not accompanied by a decline in the dispersion of productivity levels across sub-sectors. Second, from 1983 to 1993, one can observe a sharp increase in the dispersion of labour productivity worldwide, a pattern observed in every sub-sector. This implies that during this period, the β-convergencid not translate into a decline in the dispersion of productivity levels across manufacturing sub-sectors, but rather into, but rather into a σ-divergence. While caution is warranted in interpreting the causes of such a pattern, the timing is nevertheless consistent with the so-called 'lost decade', which affected many developing economies. Third, from 1993 to 2019, the dispersion of labour productivity across manufacturing sub-sectors declined sharply for all manufacturing industries, bringing dispersion back to its 1963 level. Interestingly, this descriptive evidence suggests that a relatively short episode of adverse and uneven productivity dynamics was sufficient to generate a marked increase in cross-sector dispersion, whose reversal required almost three decades, with dispersion returning to its initial 1963 level only by the end of the period. This period is thus the only one over the last sixty years during which the β-convergence process was accompanied by a process of σ-convergence.

5 Robustness checks

We conduct several robustness checks to assess the sensitivity of the results, especially the β-convergence estimates.

1. Annualised growth rates over T years. We re-estimate the same five models described in the β-convergence framework using annualised growth rates computed over 3, 5, and 10 years. This is done for both the unconditional and conditional specifications. The results are reported in the Appendix, in Tables A5, A6, and A7. Our results are robust to alternative choices of T, and the main pattern remains unchanged: labour productivity in manufacturing exhibits significant convergence, which is stronger in the post-1990 period and more pronounced in the conditional specifications. At the same time, the estimated annual convergence effect tends to decline as T increases, likely because longer horizons smooth short-run fluctuations and episodic catch-up dynamics. The estimated β-coefficients decrease from -0.052 and -0.121 for $T = 1$ to -0.029 and -0.061 for $T = 10$ in the unconditional and conditional specifications estimated on the full sample, respectively.

2. Winsorizing the data at alternative thresholds. To check whether the estimates are sensitive to extreme values and potential outliers, we winsorize labour productivity at three different thresholds, namely the 1st–99th, 2.5th–97.5th, and 5th–95th percentiles. We focus here on the annualised growth rate computed over $T = 1$ year, given the relative stability of the estimates shown in the previous step. The results are reported in the Appendix, in Tables A8, A9, and A10. The results are robust to any of these thresholds, and the main pattern of significant convergence remains largely unchanged. As expected the β-convergence estimates tend to be slightly smaller as the threshold becomes more stringent, but the differences are relatively small. For instance, the estimated β-coefficients decrease from -0.052 and -0.121 to -0.041 and -0.109, respectively, when labour productivity is winsorized at the 5th and 95th percentiles in the unconditional and conditional full-sample specifications.

3. Balanced and unbalanced panels. To assess the sensitivity of the estimates to the structure of the panel, we re-estimate each specification using alternatively a balanced panel, restricted to countries with complete data over the whole period (as in Figure A2 in the σ-convergence analysis), and the full unbalanced panel, which includes countries entering or leaving the sample over time as well as those with variation in sub-sector coverage. The results are reported in the Appendix, in Tables A11 and A12.

When focusing on the balanced panel, the results remain broadly consistent with the main findings. The picture is more contrasted for the unbalanced panel. First, the β-coefficients indicate a substantially faster convergence process in both the unconditional and conditional full-sample specifications. Yet, it seems that it is no longer accompanied by a significantly stronger increase in convergence speed after the 1990s relative to the pre-1990s period, which marks a notable departure from the baseline results. If anything, the estimates suggest that convergence may even have slowed down in the 2010s, as the interaction term for that decade is positive. However, the implied marginal effect remains largely negative, suggesting that this slowdown is not sufficient to overturn the overall convergence process. These results warrant further investigation in future versions of the paper.

4. Leave-one-out test by sub-sector. To assess whether the overall convergence results are driven by any particular manufacturing sub-sector, we re-estimate the baseline specifications while omitting each of the 12 sub-sectors in turn. The results are reported in the Appendix, in Tables A13, A14, and A15. For ease of interpretation, we report only the results for the second and sixth specifications of the β-convergence framework, which allow the convergence process to differ between the pre-1990s and post-1990s periods. Note as well that the first two columns of each table reproduces the baseline estimates reported in Table 3 and is included to facilitate interpretation of the leave-one-out results. Overall, our results are robust to the exclusion of any individual sub-sector, which is consistent with the evidence reported in Table 4 where we were estimating the individual convergence effect for each manufacturing industry. No single sub-sector, or group of activities, appears to fully drive the results and the acceleration in the post-1990s period, whether in the unconditional or the conditional specifications.

5. Leave-one-out test by region. To assess whether the overall convergence results are driven by any particular region (or group of countries), we re-estimate the baseline specifications while omitting each of the 8 regions in turn. For the details of the countries and regions, see Table A4. The results are reported in the Appendix, in Tables A16 and A17. Note that, just like in the previous step, we report only the results for the second and sixth specifications of the β-convergence framework, with the first two columns of each table reproducing the baseline estimates for ease of interpretation. Once again, our results are robust to the exclusion of any individual region, and the variation in the β-convergence estimates across specifications tends to be broadly consistent with our expectations.

When Europe and North America or Advanced Asia and Oceania are omitted, the overall convergence estimate for the rest of the sample increases, which is consistent with the idea that these regions may have slowed the convergence process given their already relatively high levels of labour productivity. Conversely, when Latin America or Sub-Saharan Africa is omitted, the overall convergence estimate declines, which is again consistent with the view that these regions may have accelerated the convergence process given their relatively low levels of labour productivity. These intuitively plausible variations do not arise in every case, however. In particular, omitting the Middle East and North Africa or Emerging Asia does not lead to lower estimates. While this warrants further investigation, it should also be noted that some regions are relatively heterogeneous in terms of the countries they include, which may help explain these more complex patterns. In a nutshell, no single region appears to entirely drive either the convergence results for the full sample or the post-1990s acceleration, whether in the unconditional or the conditional specifications.

6. STiM robustness check. Finally, we re-estimate the β-convergence specifications drop from the sample observations which have been estimated relying on a set of assumptions described in the data section. We drop data points for which either employment or value added had been linearly interpolated and data points for which employment or value added had been estimated relying on the constant labour productivity assumption. The results are reported in the Appendix, in Table A18. A comparison with the baseline estimates reported in Table 3 suggests that the results are robust to this check with nearly no change in both the magnitude and the significance of the β-convergence estimates. The loss of observations is also relatively limited moving from $T = 42,377$ to $T = 39,254$.

6 Regional heterogeneity and convergence clubs

While the previous results point to a significant (and robust) negative relationship between the initial level of labour productivity and its subsequent growth rate, it remains unclear whether this pattern of convergence characterises all regions or countries. This question is examined in the first subsection. The second subsection then investigates whether countries may converge towards different steady states, thereby forming so-called convergence clubs (Phillips and Sul, 2007).

6.1 Regional heterogeneity in β-convergence

A first approach consists of breaking down the estimates by region in order to test whether each region still exhibits a significant β-convergence effect, and whether catch-up dynamics differ across regions. We do so by relying on the same regional classification used in the robustness checks, which yields eight regions. These are Advanced Asia and Oceania (AAS), Latin America (LAM), Emerging Asia and Oceania (EAS), Europe and North America (ENA), Middle East and North Africa (MENA), Post-Soviet States (PSS), Sub-Saharan Africa (SSA) and West Indies and Other Islands (WIOI). Details on the country composition of each region are available in Table A4. To avoid overcrowding the main paper with tables, we report only specification allowing the convergence effect to vary across pre-1990s and post-1990s periods and across different technological groups[15]. We consider these two specifications to be the most relevant in this case, since they allow the coefficient to be broken down by region. Moreover, we report only the unconditional convergence setting in the main text, while the conditional convergence setting is presented in the Appendix (Tables A19 and A20).

Results are reported in Tables 6 and 7. To facilitate interpretation, the first two columns of each table report the baseline estimates for the corresponding specification in the full sample, as shown in Table 3. The remaining columns report the estimates for each region separately. Overall, the results show that the significant convergence effect in labour productivity observed in the full sample is also observed in every single region, regardless of the period considered, albeit with some variation in the magnitude of the β-coefficient. In fact, for all regions the convergence effect in the 1990s appears to be stronger than in the pre-1990s. This lends support to the view that reallocating factors of production towards the manufacturing sector may generate economy-wide gains in terms of productivity growth, regardless of the region considered. It is also worth noting that the results show once more that the significant convergence effect is not driven by any particular manufacturing sub-sectors, since nearly all interactions between the initial level of labour productivity and the technological groups are statistically insignificant. The only exceptions are mid-tech activities in the Middle East and North America (MENA) and high-tech activities in the West Indies and Other Islands (WIOI). Apart from these two cases, the evidence suggests again that the convergence effect

[15] Given the lack of data points for the Post-Soviet States before the 1990s, we do not conduct a separate analysis for these countries.

Table 6: Unconditional β-convergence estimates for labour productivity in manufacturing sub-sectors, per regions

	Full Sample		Only AAS		Only LAM		Only EAS		Only ENA	
	(2)	(4)	(2)	(4)	(2)	(4)	(2)	(4)	(2)	(4)
Initial value (L1)	-0.024***	-0.044***	-0.043***	-0.051***	-0.109***	-0.160***	-0.028***	-0.051***	-0.033***	-0.044***
	(0.003)	(0.004)	(0.007)	(0.013)	(0.015)	(0.029)	(0.009)	(0.012)	(0.006)	(0.007)
×Post-1990s	-0.040***		-0.027**		-0.110***		-0.037***		-0.023***	
	(0.004)		(0.013)		(0.028)		(0.011)		(0.007)	
×Mid-tech		-0.013**		-0.005		-0.032		0.005		-0.011
		(0.006)		(0.016)		(0.040)		(0.015)		(0.009)
×High-tech		-0.012*		-0.009		-0.014		-0.020		-0.012
		(0.006)		(0.017)		(0.043)		(0.019)		(0.011)
Constant	0.539***	0.561***	0.686***	0.640***	1.883***	1.849***	0.515***	0.548***	0.523***	0.576***
	(0.026)	(0.027)	(0.086)	(0.071)	(0.175)	(0.175)	(0.062)	(0.065)	(0.041)	(0.045)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No	No	No
Observations	42,377	42,377	3,256	3,256	4,816	4,816	7,649	7,649	13,663	13,663
Adj-R2	0.074	0.070	0.250	0.248	0.231	0.223	0.134	0.132	0.167	0.166

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). For the correspondence between the country and the region omitted, see Table A4. The abbreviations are defined as follows: AAS denotes Advanced Asia and Oceania, LAM Latin America, EAS Emerging Asia and Oceania, and ENA Europe and North America. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. The conditional convergence setting of this Table is available in the Appendix, Table A19. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 7: Unconditional β-convergence estimates for labour productivity in manufacturing sub-sectors, per regions

	Full Sample		Only MENA		Only SSA		Only WIOI	
	(2)	(4)	(2)	(4)	(2)	(4)	(2)	(4)
Initial value (L1)	-0.024***	-0.044***	-0.019***	-0.032***	-0.028***	-0.072***	-0.171***	-0.047***
	(0.003)	(0.004)	(0.004)	(0.006)	(0.011)	(0.011)	(0.038)	(0.015)
$\times$Post-1990s	-0.040***		-0.040***		-0.092***		0.129***	
	(0.004)		(0.008)		(0.017)		(0.042)	
$\times$Mid-tech		-0.013**		-0.021*		-0.004		-0.020
		(0.006)		(0.012)		(0.021)		(0.026)
$\times$High-tech		-0.012*		-0.005		-0.007		0.049***
		(0.006)		(0.010)		(0.045)		(0.015)
Constant	0.539***	0.561***	0.456***	0.414***	0.783***	0.717***	0.743***	0.391***
	(0.026)	(0.027)	(0.060)	(0.053)	(0.116)	(0.115)	(0.125)	(0.090)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	No	No	No
Observations	42,377	42,377	4,520	4,520	3,543	3,543	567	567
Adj-R2	0.074	0.070	0.153	0.150	0.228	0.217	0.512	0.511

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). For the correspondence between the country and the region omitted, see Table A4. The abbreviations are defined as follows: MENA denotes Middle East and North Africa, PSS Post-Soviet States, SSA Sub-Saharan Africa, and WIOI West Indies and Other Islands. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. The conditional convergence setting of this Table is available in the Appendix, Table A20. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

is broad-based across manufacturing sub-sectors, regardless of the region considered. These two patterns also hold in the conditional convergence setting reported in the Appendix[16].

Looking at the regional results, three stylized facts emerge. First, the regions previously classified as developed in the descriptive statistics — namely, Advanced Asia and Oceania and Europe and North America — appear to have experienced stronger catch-up than the full sample before the 1990s, but weaker catch-up thereafter. This is consistent with the view that the bulk of the catch-up process in these regions took place before the 1990s, especially in Europe during the 'Thirty Glorious Years' (Fourastié, 1979). Somewhat surprisingly, Emerging Asia and Oceania displays a similar pattern and therefore appears to belong to the same group. Second, only one region exhibits the opposite pattern, with a weaker convergence effect before the 1990s and a stronger one thereafter relative to the full sample. This is the case for the Middle East and North Africa, whose post-1990s coefficient is identical to that of the baseline in Table 3. Lastly, three developing regions — Latin America, Sub-Saharan Africa, and the West Indies and Other Islands — display a convergence speed higher than that of the full sample in both periods. Interestingly, the convergence effect is stronger in regions that are often considered particularly prone to premature deindustrialisation (Castillo and Neto, 2016; Rodrik, 2016; Kruse et al., 2022; Nguimkeu and Zeufack, 2024), suggesting that the potential gains from reallocating factors of production towards manufacturing sub-sectors may be especially large in these regions[17]. These stylized facts broadly align with the conditional convergence results reported in the Appendix.

6.2 The convergence club approach

A second approach consists in testing whether countries may converge towards different steady states, thereby forming so-called convergence clubs. To do so, we rely on the methodology developed by Phillips and Sul (2007), which is based on a non-linear factor model. While other convergence procedures group economies a priori, without relying on a specific identification method, the log t test developed by Phillips and Sul (2007) identifies convergence clubs endogenously, on the basis of unobserved factors shaping the transition paths of the units considered. In other words, whenever full-panel convergence is rejected, this procedure provides a data-driven clustering algorithm that can be used to identify convergence clubs[18].

We thus apply this log t test to our sample of 175 countries and 12 manufacturing sub-sectors over the period 1963–2019. As the methodology is best implemented on a balanced panel, we first construct such a panel by averaging productivity levels within technological groups and keeping only countries for which data are available continu-

[16]The only difference with the unconditional setting concerns Emerging Asia and Oceania, where the convergence effect does not appear to strengthen after the 1990s.

[17]We are aware of recent evidence suggesting that Sub-Saharan Africa may have begun to reverse this trend, raising the possibility that these countries could benefit from substantial productivity gains in the future if they continue to reindustrialise successfully.

[18]More detail regarding this test can be found in Phillips and Sul (2007).

ously from 1963 to 2019. We therefore obtain annual country-level observations for each technological group over the whole period. The log t test is then run separately within each technological group to determine whether the convergence process observed is directed towards a common steady state or whether distinct convergence clubs can be identified. The results are reported in Table 8.

Table 8: Phillips–Sul log t test by technological group

	Low-tech	Mid-tech	High-tech
Coefficient	-0.0490	0.1653	-0.4960
	(0.2652)	(0.2695)	(0.3353)
t-statistic	-0.1847	0.6134	-1.4794

The t-statistics for the three technological groups suggest that the null hypothesis of convergence cannot be rejected at the 5% level, using the one-sided critical value of -1.65, implying that the convergence process under way appears to be directed towards a single common steady state. To be clear, this does not mean that the log t test rejects convergence as understood in the β framework; rather, it suggests that, within each technological group, the productivity paths observed in the balanced panel are consistent with convergence towards a common long-run steady state, with no clear evidence of distinct convergence clubs across countries. As such, no convergence clubs appear to be identified in our baseline sample[19].

7 Final discussions

Final estimates of this paper strongly suggest that labour productivity in manufacturing exhibits convergence, with faster convergence after the 1990s and little variation across manufacturing sub-sectors. This suggests that manufacturing remains an important sector for developing countries at an early stage of development (where productivity is low), and may constitute an even stronger locus of productivity catch-up than in the past, regardless of the sub-sector considered. At the same time, this evidence needs to be discussed in light of the recent literature on premature deindustrialisation, which argues that manufacturing is a more difficult route to growth than in the past.

Our view is that their finding of a shift in the turning point towards lower income levels in the classic hump-shaped relationship is not inconsistent with our evidence of faster convergence over the same period; quite the opposite. Usually, the main argument put forward to explain the premature deindustrialisation phenomenon is that the major

[19]This conclusion should nevertheless be interpreted with caution. In particular, the requirement to work with a balanced panel may partly explain why no convergence clubs are identified in the baseline specification. Moreover, in the high-tech group, the results appear to be sensitive to the specification adopted and, in particular, to the treatment of cyclical fluctuations. In some cases, alternative specifications suggest that a club structure may emerge.

technological and institutional changes of the 1980s and 1990s made it more difficult for countries to initiate industrialisation or to maintain a large manufacturing sector. Indeed, with the fragmentation of production processes and the expansion of global value chains, it has become more difficult for a single country to concentrate as many manufacturing activities as in the past, as industrial production is increasingly split across countries according to different stages of production (Baldwin, 2011). At the same time, the generalized intensification of globalisation, together with the reduction in tariff barriers, has lowered the cost of accessing manufacturing goods. As suggested by Rodrik (2016), these changes, may have led small developing countries to import their deindustrialisation.

That said, these same transformations may also have increased the scope for faster labour productivity convergence in manufacturing. By the same logic, they made it easier than ever for countries to integrate into specific segments of global value chains and to access capital goods at lower cost. This interpretation is consistent with firm-level evidence from some developing countries, where relatively large firms appear to enjoy particularly strong productivity growth in comparison with their smaller counterparts (Diao, Ellis et al., 2025). In this sense, the same transformations that made deindustrialisation 'premature' may also have strengthened the scope for convergence within manufacturing. In such a context, countries that succeed in maintaining relatively high manufacturing shares, or in delaying deindustrialisation, may still reap substantial gains in economy-wide productivity growth, provided that other aggregate sectors did not have performed comparatively worse.

The key remaining question is therefore under what conditions countries can initiate industrialisation, sustain a large manufacturing sector, and delay the downward shift in the turning point. As the experience of East Asian countries suggests, there is room to navigate these twin forces discussed above — simultaneously pushing towards faster convergence and towards a premature decline in manufacturing shares. One way to do so might be to ensure that domestic manufacturing remains sufficiently competitive in export markets, thereby helping to delay the traditional internal forces leading to deindustrialisation (e.g., Engel's law). In this respect, the emerging literature on industrial policy may also provide useful insights, especially regarding policies aimed at supporting manufacturing (Chang and Andreoni, 2020; Juhász and Lane, 2024).

8 Conclusions

This paper investigates the extent to which manufacturing exhibited labour productivity convergence across 175 countries and 12 manufacturing sub-sectors over the period 1963-2019. Relying on a newly harmonised dataset, the findings suggest that the β-convergence hypothesis holds for manufacturing, implying a significant and robust negative relationship between initial productivity levels and subsequent growth rates. Moreover, when allowing the β parameter to vary across sub-periods, the results show that the speed of convergence appears to have increased after the 1990s, with particularly strong increases in the 1990s and the 2000s. While one might have expected this effect to be driven by a small subset of manufacturing sub-sectors, the evidence suggests that the increase in convergence is widespread across sub-sectors, even those often considered more traditional or classified as low-tech industries. These evidence suggest that manufacturing remains an important sector for developing countries at an early stage of development (where productivity is usually low), and may constitute an even stronger locus of productivity catch-up than in the past, provided that other aggregate sectors have not performed comparatively worse.

While these results hold up after several robustness checks, we also show that drawing conclusions solely on the basis of β-convergence estimates may be quite misleading. In particular, when looking at the dispersion of productivity levels within manufacturing activities, σ-convergence occurred hand in hand with β-convergence only during the last thirty years. In fact, the dispersion of productivity levels within manufacturing was in 2019, on average, at almost exactly the same level as sixty years ago. It sheds light on the fact that a short ten-year episode of adverse and uneven productivity dynamics (1983-1993) was sufficient to generate such a marked increase in cross-sector dispersion that its reversal required almost three decades. Lastly, the convergence club analysis suggests that global convergence cannot be rejected, implying that all countries converge towards a common steady state within each technological group.

While we believe that these results are informative and robust at the current stage of this draft, we also acknowledge that they remain preliminary and that further work is needed to better understand the underlying mechanisms at play. In particular, we plan to disentangle the different sources of productivity growth in order to better understand the convergence process, notably by using shift-share decompositions (Wong, 2006; M. S. McMillan and Rodrik, 2011). We are also working to further refine the convergence club analysis and the final discussion of the twin forces that have been at work since the 1990s, simultaneously fostering faster convergence while contributing to a premature decline in manufacturing shares. Moreover, we are aware of some potential limitations related to the STiM dataset. In particular, there might still be some measurement errors affecting the estimation of productivity levels, as the baseline level of the series is based on surveys of formally registered firms (Herrendorf et al., 2026)[20]. Additionally, the method of deflating nominal values could be further improved, even though we rely on price indices at the precise sub-sectoral level when possible. These limitations are expected to be addressed (at least partially) in a future version of the STiM dataset. Nevertheless, these limits are also the consequence of the scope of this analysis, which aims to be as exhaustive as possible by compiling and harmonising 12 different data sources in order to conduct an investigation at the level of manufacturing

[20]We recently came across this paper, which appears to reach conclusions different from ours. Part of its critique concerns UNIDO surveys and their inability to capture informality. A subsequent version of this paper will engage with these arguments. However, their analysis is conducted at the aggregate manufacturing level and does not extend prior to the 1990s, making it impossible to study either cross-subsector heterogeneity or temporal heterogeneity.

sub-sectors themselves. Finally, we recall that the dataset is intended to be made publicly available, and we are committed to sharing it as soon as possible.

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9 Appendix

Table A1: Concordance between STiM and major industrial classifications

STiM, V1	**ISIC, Rev. 3.1**	**ISIC, Rev. 3**	**ISIC, Rev. 4**	**NACE 2**
1	15, 16	15, 16	10+11, 12	10+11, 12
2	17, 18, 19	17, 18, 19	13, 14, 15	13, 14, 15
3	20	20	16	16
4	21, 22	21, 22	17, 18	17, 18
5	23	23	19	19
6	24	24	20+21	20+21
7	25	25	22	22
8	26	26	23	23
9	27, 28	27, 28	24, 25	24, 25
10	29, 30, 31, 32, 33	29, 30, 31, 32, 33	28, 26, 27, 26, 26	28, 26, 27, 26, 26
11	34, 35	34, 35	29, 30	29, 30
12	36, 37	36	31+32+33	31+32+33

Note: This correspondence table is indirectly based on Pahl and M. P. Timmer (2020) and Horvát and Webb (2020) as discussed in (Bekhti, 2025). Labels for each sub-sector are provided in Table 2.

Table A2: Summary of the characteristics of each dataset used to construct the STiM database

Database	**Aggregation level**	**ISIC**	**NVA reporting**	**Out. reporting**	**Emp. reporting**	**LCU/Dollars**
INDSTAT	Disaggregated	Rev 3.1	Mix	Mix	Both	Current LCU
OECD STAN	Disaggregated	Rev 4	Basic p.	Basic p.	Both	Current LCU
OECD TiVA	Disaggregated	Rev 4	Basic p.	Basic p.	—	Current Dollars^{PWT}
OECD TiM	Disaggregated	Rev 4	—	—	Engaged	—
EU KLEMS	Disaggregated	Rev 4	Basic p.	Basic p.	Employees	Current LCU
ECLAC BADECON	Disaggregated	Rev 4	Unknown	Unknown	Unknown	Current Dollars^{PWT}
GGDC WIOD	Disaggregated	Rev 4	Basic p.	Basic p.	—	Current Dollars^{OG}
GGDC H-WIOD	Disaggregated	Rev 3.1	Producers p.	Producers p.	—	Current Dollars^{PWT}
APO	Disaggregated	Rev 4	Basic p.	—	Engaged	Current LCU
10SD/ASD/ETD	Aggregated	Rev 3.1	Basic p.	—	Engaged	Current LCU
ETD-TE	Aggregated	Rev 4	Basic p.	—	Engaged	Current LCU
WDI (World Bank)	Aggregated	Mix	Unknown	—	—	Current LCU

Note: This table reports the main characteristics of each source used to build the STiM database. The two columns 'NVA reporting' and 'Out. reporting' indicate whether value added and output are reported at basic prices, at factor cost, at producer prices, or as a mix of these different valuation methods. The column 'Employment reporting' indicates whether employment is reported as the number of employees, the number of persons engaged, or both. Note that if coverage is the same, we prefer basic prices over other valuation methods and employment reported as the number of employees over persons engaged. The last column indicates whether monetary variables are natively reported in local currency units (LCU) or in current US dollars. In the latter case, we specify whether the conversion relies on the Penn World Table (PWT). If 'OG' is specified, it means we have used original exchange rates (i.e., those that have been used to provide dollar estimates) to convert from dollars to LCU.

Table A3: Priority rules for combining growth rates across sources and valuation methods

	Employment growth rates		Value-added growth rates		Output growth rates	
Priority	Source	Measurement	Source	Valuation	Source	Valuation
1	UNIDO	Nb. employees	UNIDO	Basic prices	UNIDO	Basic prices
2	OECD STAN	Nb. employees	OECD STAN	Basic prices	OECD STAN	Basic prices
3	EU-KLEMS	Nb. employees	OECD TiVA	Basic prices	OECD TiVA	Basic prices
4	APO	Nb. employees	GGDC (WIOD)	Basic prices	GGDC (WIOD)	Basic prices
5	UNIDO	Persons engaged	EU-KLEMS	Basic prices	EU-KLEMS	Basic prices
6	OECD STAN	Persons engaged	APO	Basic prices	UNIDO	Producer prices
7	OECD TiM	Persons engaged	UNIDO	Producer prices	GGDC (H-WIOD)	Producer prices
8	CEPAL Badecon	Unknown	GGDC (H-WIOD)	Producer prices	UNIDO	Factor cost
9	–	–	UNIDO	Factor cost	UNIDO	Unknown
10	–	–	UNIDO	Unknown	CEPAL Badecon	Unknown
11	–	–	CEPAL Badecon	Unknown	–	–

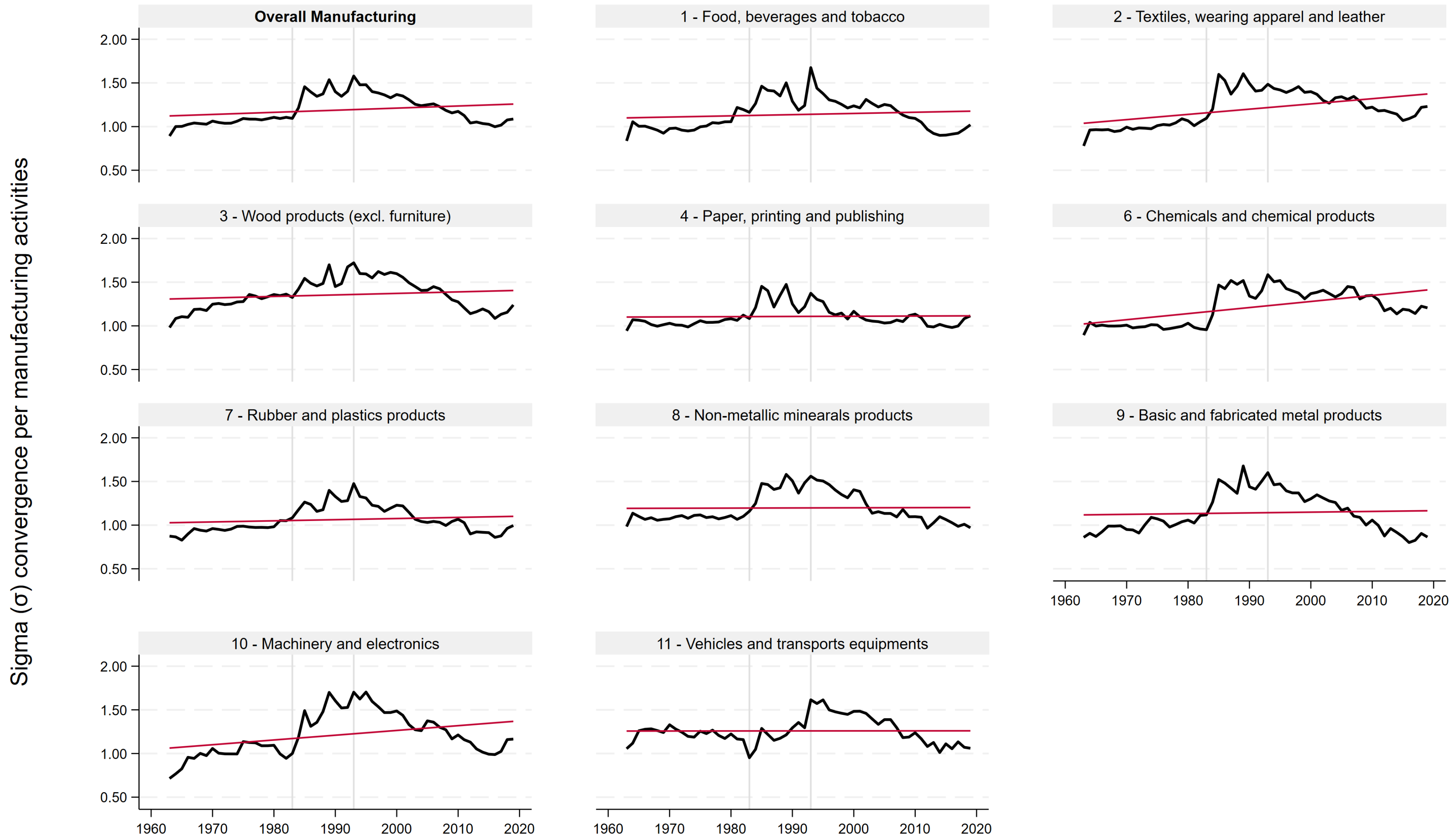
Notes: Priority levels indicate the deterministic order in which growth rates are selected for each country–year. Within each block, the first available growth rate according to this hierarchy is retained. UNIDO acts as the primary source whenever comparable definitions are available. For aggregated datasets, GGDC series are preferred to WDI indicators.

Table A4: Summary of Regions with Country Names

Regions	**Country names**	**Total**
Advanced Asia and Oceania (AAS)	Australia, China - Hong Kong SAR, China - Taiwan Province, Japan, New Zealand, Republic of Korea	6
Emerging Asia and Oceania (EAS)	Afghanistan, Bangladesh, Bhutan, Brunei Darussalam, Cambodia, China, China - Macao SAR, Cyprus, India, Indonesia, Lao People's Dem Rep, Malaysia, Mongolia, Myanmar, Nepal, Pakistan, Papua New Guinea, Philippines, Singapore, Sri Lanka, Thailand, Turkiye, Viet Nam	24
Europe and North America (ENA)	Albania, Austria, Belgium, Bulgaria, Canada, Denmark, Finland, France, Germany, Germany - Fed Rep, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, North Macedonia, Norway, Poland, Portugal, Republic of Moldova, Romania, Spain, Sweden, Switzerland, United Kingdom, United States of America	29
Latin America (LAM)	Argentina, Belize, Bolivia (Plurinational State of), Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Guyana, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Uruguay, Venezuela (Bolivarian Republic of)	20
Middle-East and North-Africa (MENA)	Algeria, Bahrain, Egypt, Iran (Islamic Republic of), Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Qatar, Saudi Arabia, State of Palestine, Syrian Arab Republic, Tunisia, United Arab Emirates, Yemen	19
Post-Soviet States (PSS)	Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Croatia, Czechia, Czechoslovakia, Estonia, Georgia, Germany - Dem Rep, Kazakhstan, Kosovo, Kyrgyzstan, Latvia, Lithuania, Montenegro, Russian Federation, Serbia, Serbia and Montenegro, Slovakia, Slovenia, Tajikistan, USSR, Ukraine, Uzbekistan, Yugoslavia	26
Sub-Saharan Africa (SSA)	Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Central African Republic, Congo, Côte d'Ivoire, Eritrea, Eswatini, Ethiopia, Ethiopia and Eritrea, Former Sudan, Gabon, Gambia, Ghana, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Somalia, South Africa, Uganda, United Republic of Tanzania, Zambia, Zimbabwe	35
West Indies and other islands (WIOI)	Aruba, Bahamas, Barbados, Bermuda, Cabo Verde, Cuba, Dominican Republic, Fiji, Haiti, Jamaica, Maldives, Mauritius, Puerto Rico, Saint Lucia, Tonga, Trinidad and Tobago	16

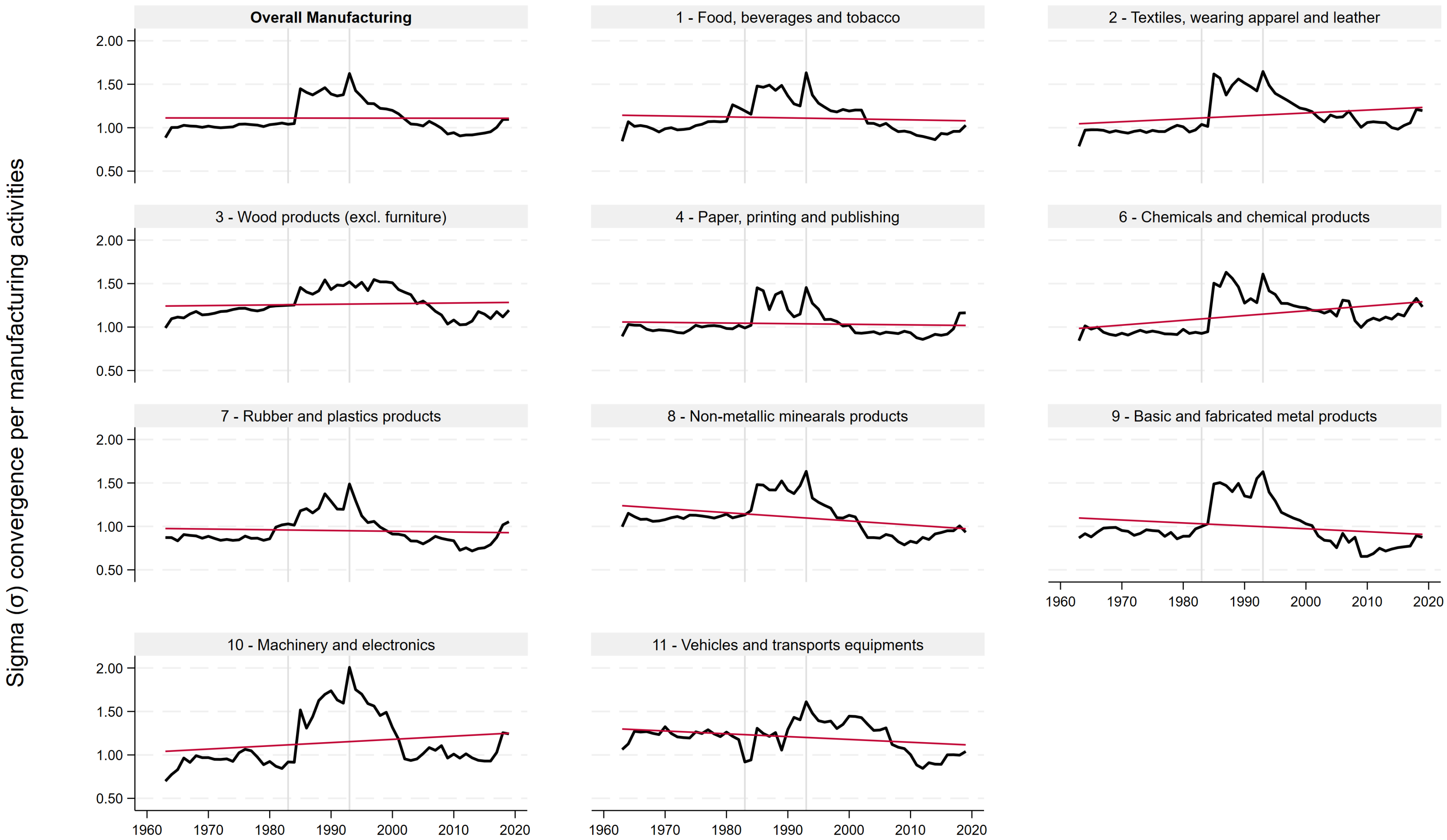
Note: This table reports the country composition of each broad region used in the paper. To classify countries into broader areas, we adapt the traditional MARC classification system. First, Asia is divided into *Advanced Asia and Oceania* and *Emerging Asia and Oceania*, following the CEPII classification. Second, we apply a similar approach to Africa by grouping 19 economies into the *Middle-East and North-Africa* region, following the latest UNICEF classification. The remaining African countries are classified under *Sub-Saharan Africa*. Third, we define a separate *Post-Soviet States* region, encompassing former communist countries in both Europe and Central Asia. Fourth, we group all islands located in the Caribbean, the Atlantic Ocean, and the Indian Ocean into a single region labelled *West Indies and Other Islands*. Finally, we combine *North America* with *Europe* and define *Latin America* as the group of countries corresponding to the conventional MARC classification of South and Central America, with the addition of Mexico.

Figure A1: σ-convergence across manufacturing sub-sectors, without sub-sector number 5 (oil, fuel, and gas extraction)



Notes: This figure plots the evolution of the standard deviation of the log of labour productivity across manufacturing sub-sectors and countries from 1963 to 2019. Note that this figure is based on the same sample as the β-convergence analysis, i.e., an unbalanced panel, simply omitting the sub-sector number 5 (coke, refined petroleum, nuclear fuel) and 12 (recycling and other manufacturing activities).

Figure A2: σ-convergence across manufacturing sub-sectors, balanced panel



Notes: This figure plots the evolution of the standard deviation of the log of labour productivity across manufacturing sub-sectors and countries from 1963 to 2019. Note that this figure is based on a perfectly balanced sample to avoid any bias in the estimation of the standard deviation.

Table A5: β-convergence estimates for labour productivity in manufacturing sub-sectors ($T = 3$)

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Labour productivity (L3)	-0.041***	-0.019***	-0.011**	-0.035***	-0.035***	-0.092***	-0.076***	-0.070***	-0.092***	-0.098***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)
×Post-1990s		-0.030***					-0.021***			
		(0.003)					(0.003)			
×1970*s*			-0.003					-0.005		
			(0.005)					(0.005)		
×1980*s*			-0.013**					-0.008		
			(0.005)					(0.005)		
×1990*s*			-0.050***					-0.030***		
			(0.006)					(0.005)		
×2000*s*			-0.035***					-0.025***		
			(0.005)					(0.005)		
×2010*s*			-0.027***					-0.025***		
			(0.006)					(0.006)		
×Mid-tech				-0.009**	-0.008*				0.002	-0.010***
				(0.004)	(0.004)				(0.003)	(0.003)
×High-tech				-0.010**	-0.010**				-0.001	-0.000
				(0.005)	(0.005)				(0.004)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	40,099	40,099	40,099	40,099	36,994	40,099	40,099	40,099	40,099	36,994
Adj-R2	0.127	0.134	0.138	0.127	0.130	0.231	0.234	0.235	0.231	0.254

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 3$). Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A6: β-convergence estimates for labour productivity in manufacturing sub-sectors ($T = 5$)

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Labour productivity (L5)	-0.036***	-0.011***	-0.008**	-0.031***	-0.031***	-0.079***	-0.061***	-0.057***	-0.080***	-0.085***
	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
×Post-1990s		-0.032***					-0.023***			
		(0.003)					(0.003)			
×1970*s*			-0.002					-0.004		
			(0.004)					(0.004)		
×1980*s*			-0.004					-0.004		
			(0.005)					(0.004)		
×1990*s*			-0.041***					-0.027***		
			(0.005)					(0.004)		
×2000*s*			-0.034***					-0.025***		
			(0.005)					(0.004)		
×2010*s*			-0.030***					-0.028***		
			(0.005)					(0.005)		
×Mid-tech				-0.007**	-0.007*				0.001	-0.008***
				(0.003)	(0.003)				(0.003)	(0.002)
×High-tech				-0.008**	-0.008**				-0.001	0.000
				(0.004)	(0.004)				(0.003)	(0.003)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	37,877	37,877	37,877	37,877	34,945	37,877	37,877	37,877	37,877	34,945
Adj-R2	0.169	0.185	0.186	0.170	0.174	0.308	0.315	0.315	0.308	0.337

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 5$). Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A7: β-convergence estimates for labour productivity in manufacturing sub-sectors ($T = 10$)

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Labour productivity (L10)	-0.029***	-0.009***	-0.009***	-0.025***	-0.025***	-0.061***	-0.047***	-0.047***	-0.061***	-0.065***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
×Post-1990s		-0.025***					-0.016***			
		(0.002)					(0.002)			
×1970*s*			0.000					0.000		
			(.)					(.)		
×1980*s*			0.001					-0.000		
			(0.003)					(0.003)		
×1990*s*			-0.017***					-0.010***		
			(0.003)					(0.003)		
×2000*s*			-0.029***					-0.019***		
			(0.003)					(0.002)		
×2010*s*			-0.024***					-0.020***		
			(0.003)					(0.003)		
×Mid-tech				-0.006**	-0.004*				0.000	-0.005***
				(0.003)	(0.003)				(0.002)	(0.002)
×High-tech				-0.006**	-0.006**				-0.000	0.000
				(0.003)	(0.003)				(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	32,653	32,653	32,653	32,653	30,122	32,653	32,653	32,653	32,653	30,122
Adj-R2	0.248	0.268	0.271	0.250	0.250	0.437	0.444	0.446	0.437	0.470

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 10$). Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A8: β-convergence estimates for labour productivity in manufacturing sub-sectors, winsorized at the 1st and 99th percentiles

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial value (L1)	-0.048***	-0.023***	-0.013***	-0.038***	-0.038***	-0.116***	-0.095***	-0.087***	-0.113***	-0.117***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
×Post-1990s		-0.035***					-0.029***			
		(0.004)					(0.004)			
×1970*s*			-0.007					-0.010*		
			(0.005)					(0.005)		
×1980*s*			-0.016***					-0.008		
			(0.005)					(0.005)		
×1990*s*			-0.065***					-0.043***		
			(0.006)					(0.006)		
×2000*s*			-0.040***					-0.032***		
			(0.006)					(0.006)		
×2010*s*			-0.026***					-0.027***		
			(0.006)					(0.007)		
×Mid-tech				-0.016***	-0.012**				-0.005	-0.014***
				(0.005)	(0.005)				(0.005)	(0.004)
×High-tech				-0.014**	-0.014**				-0.004	-0.003
				(0.006)	(0.006)				(0.005)	(0.005)
Constant	0.516***	0.499***	0.473***	0.516***	0.491***	1.203***	1.182***	1.163***	1.201***	1.256***
	(0.024)	(0.023)	(0.022)	(0.024)	(0.023)	(0.050)	(0.049)	(0.050)	(0.050)	(0.047)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	42,377	42,377	42,377	42,377	39,096	42,377	42,377	42,377	42,377	39,096
Adj-R2	0.065	0.069	0.071	0.066	0.067	0.110	0.112	0.113	0.111	0.118

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Labour productivity is winsorized at the 1st and 99th percentiles. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A9: β-convergence estimates for labour productivity in manufacturing sub-sectors, winsorized at the 2.5th and 97.5th percentiles

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial value (L1)	-0.044***	-0.022***	-0.012***	-0.033***	-0.033***	-0.112***	-0.092***	-0.085***	-0.106***	-0.108***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
×Post-1990s		-0.031***					-0.027***			
		(0.003)					(0.004)			
×1970*s*			-0.008*					-0.010**		
			(0.005)					(0.004)		
×1980*s*			-0.015***					-0.008		
			(0.005)					(0.005)		
×1990*s*			-0.053***					-0.036***		
			(0.005)					(0.005)		
×2000*s*			-0.040***					-0.035***		
			(0.005)					(0.006)		
×2010*s*			-0.028***					-0.033***		
			(0.006)					(0.007)		
×Mid-tech				-0.019***	-0.011**				-0.010**	-0.012***
				(0.005)	(0.004)				(0.004)	(0.004)
×High-tech				-0.016***	-0.016***				-0.006	-0.005
				(0.005)	(0.005)				(0.004)	(0.004)
Constant	0.471***	0.457***	0.442***	0.472***	0.435***	1.161***	1.144***	1.140***	1.158***	1.167***
	(0.022)	(0.021)	(0.021)	(0.022)	(0.020)	(0.049)	(0.048)	(0.049)	(0.048)	(0.044)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	42,377	42,377	42,377	42,377	39,096	42,377	42,377	42,377	42,377	39,096
Adj-R2	0.062	0.065	0.066	0.063	0.063	0.104	0.106	0.106	0.104	0.108

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Labour productivity is winsorized at the 2.5th and 97.5th percentiles. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A10: β-convergence estimates for labour productivity in manufacturing sub-sectors, winsorized at the 5th and 95th percentiles

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial value (L1)	-0.041***	-0.021***	-0.011***	-0.029***	-0.029***	-0.109***	-0.090***	-0.082***	-0.102***	-0.103***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
×Post-1990s		-0.028***					-0.026***			
		(0.003)					(0.004)			
×1970*s*			-0.010**					-0.011***		
			(0.004)					(0.004)		
×1980*s*			-0.014***					-0.009**		
			(0.005)					(0.004)		
×1990*s*			-0.045***					-0.031***		
			(0.005)					(0.005)		
×2000*s*			-0.040***					-0.038***		
			(0.005)					(0.005)		
×2010*s*			-0.029***					-0.036***		
			(0.005)					(0.006)		
×Mid-tech				-0.020***	-0.011***				-0.013***	-0.010***
				(0.005)	(0.004)				(0.004)	(0.004)
×High-tech				-0.016***	-0.016***				-0.007*	-0.007*
				(0.005)	(0.005)				(0.004)	(0.004)
Constant	0.436***	0.425***	0.416***	0.438***	0.397***	1.128***	1.115***	1.118***	1.127***	1.116***
	(0.021)	(0.020)	(0.020)	(0.021)	(0.018)	(0.048)	(0.048)	(0.048)	(0.048)	(0.043)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	42,377	42,377	42,377	42,377	39,096	42,377	42,377	42,377	42,377	39,096
Adj-R2	0.060	0.062	0.063	0.061	0.061	0.101	0.102	0.102	0.101	0.103

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Labour productivity is winsorized at the 5th and 95th percentiles. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A11: β-convergence estimates for labour productivity in manufacturing sub-sectors, balanced panel.

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial value (L1)	-0.041***	-0.018***	-0.013***	-0.033***	-0.033***	-0.109***	-0.089***	-0.085***	-0.104***	-0.112***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)
×Post-1990s		-0.042***					-0.032***			
		(0.004)					(0.004)			
×1970*s*			-0.005					-0.009		
			(0.005)					(0.005)		
×1980*s*			-0.007					-0.002		
			(0.005)					(0.005)		
×1990*s*			-0.055***					-0.036***		
			(0.007)					(0.007)		
×2000*s*			-0.053***					-0.047***		
			(0.007)					(0.007)		
×2010*s*			-0.023**					-0.022**		
			(0.010)					(0.010)		
×Mid-tech				-0.016**	-0.009				-0.008	-0.017***
				(0.006)	(0.007)				(0.006)	(0.005)
×High-tech				-0.011	-0.011				-0.006	-0.005
				(0.007)	(0.007)				(0.006)	(0.006)
Constant	0.452***	0.447***	0.426***	0.454***	0.419***	1.153***	1.128***	1.123***	1.151***	1.233***
	(0.030)	(0.029)	(0.030)	(0.030)	(0.030)	(0.060)	(0.058)	(0.060)	(0.060)	(0.061)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	28,961	28,961	28,961	28,961	26,659	28,961	28,961	28,961	28,961	26,659
Adj-R2	0.078	0.084	0.085	0.079	0.076	0.121	0.124	0.124	0.121	0.126

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Estimates are based on a balanced panel. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A12: β-convergence estimates for labour productivity in manufacturing sub-sectors, unbalanced panel.

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial value (L1)	-0.079***	-0.069***	-0.067***	-0.071***	-0.071***	-0.141***	-0.127***	-0.182***	-0.149***	-0.150***
	(0.006)	(0.011)	(0.006)	(0.009)	(0.009)	(0.010)	(0.011)	(0.032)	(0.011)	(0.012)
×Post-1990s		-0.011					-0.016			
		(0.011)					(0.012)			
×1970*s*			0.029**					0.059**		
			(0.011)					(0.030)		
×1980*s*			-0.011					0.054		
			(0.015)					(0.034)		
×1990*s*			-0.069***					0.004		
			(0.014)					(0.035)		
×2000*s*			0.006					0.060*		
			(0.009)					(0.034)		
×2010*s*			0.022**					0.064*		
			(0.010)					(0.035)		
×Mid-tech				-0.009	-0.008				0.014	-0.004
				(0.013)	(0.013)				(0.012)	(0.012)
×High-tech				-0.017	-0.017				0.005	0.006
				(0.014)	(0.014)				(0.013)	(0.013)
Constant	0.815***	0.811***	0.738***	0.814***	0.804***	1.420***	1.417***	1.337***	1.431***	1.484***
	(0.057)	(0.057)	(0.050)	(0.056)	(0.055)	(0.095)	(0.094)	(0.092)	(0.092)	(0.090)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	13,355	13,355	13,355	13,355	12,379	13,355	13,355	13,355	13,355	12,379
Adj-R2	0.103	0.103	0.115	0.103	0.107	0.152	0.152	0.158	0.153	0.165

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Estimates are based only on an unbalanced panel. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A13: β-convergence estimates for labour productivity in manufacturing sub-sectors, leave-one-out test by sub-sector.

	Full Sample		W/O S1		W/O S2		W/O S3		W/O S4	
	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Initial value (L1)	-0.024***	-0.098***	-0.025***	-0.103***	-0.017***	-0.087***	-0.026***	-0.099***	-0.031***	-0.100***
	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)	(0.006)	(0.004)	(0.006)
$\times$Post-1990s	-0.040***	-0.031***	-0.043***	-0.031***	-0.039***	-0.028***	-0.040***	-0.035***	-0.043***	-0.032***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Constant	0.539***	1.230***	0.566***	1.274***	0.455***	1.097***	0.573***	1.290***	0.621***	1.227***
	(0.026)	(0.052)	(0.028)	(0.056)	(0.022)	(0.052)	(0.030)	(0.062)	(0.035)	(0.061)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	42,377	42,377	39,071	39,071	37,535	37,535	34,724	34,724	28,692	28,692
Adj-R2	0.074	0.120	0.077	0.125	0.075	0.119	0.081	0.127	0.076	0.119

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Each sub-sector is dropped in turn and the model is re-estimated. For the correspondence between the sub-sector omitted and the label used in the table, see Table 2. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A14: β-convergence estimates for labour productivity in manufacturing sub-sectors, leave-one-out test by sub-sector.

	Full Sample		W/O S5		W/O S6		W/O S7		W/O S8	
	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Initial value (L1)	-0.024***	-0.098***	-0.027***	-0.099***	-0.024***	-0.098***	-0.025***	-0.098***	-0.024***	-0.097***
	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
×Post-1990s	-0.040***	-0.031***	-0.038***	-0.033***	-0.037***	-0.032***	-0.039***	-0.030***	-0.040***	-0.033***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.539***	1.230***	0.558***	1.261***	0.504***	1.224***	0.551***	1.239***	0.541***	1.235***
	(0.026)	(0.052)	(0.027)	(0.059)	(0.027)	(0.052)	(0.027)	(0.055)	(0.026)	(0.053)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	42,377	42,377	37,855	37,855	38,309	38,309	38,820	38,820	41,611	41,611
Adj-R2	0.074	0.120	0.080	0.127	0.070	0.116	0.080	0.126	0.074	0.121

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Each sub-sector is dropped in turn and the model is re-estimated. For the correspondence between the sub-sector omitted and the label used in the table, see Table 2. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A15: β-convergence estimates for labour productivity in manufacturing sub-sectors, leave-one-out test by sub-sector.

	Full Sample		W/O S9		W/O S10		W/O S11		W/O S12	
	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Initial value (L1)	-0.024***	-0.098***	-0.025***	-0.098***	-0.024***	-0.097***	-0.023***	-0.098***	-0.024***	-0.098***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
$\times$Post-1990s	-0.040***	-0.031***	-0.039***	-0.030***	-0.040***	-0.033***	-0.040***	-0.030***	-0.040***	-0.032***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.539***	1.230***	0.551***	1.239***	0.541***	1.235***	0.530***	1.225***	0.540***	1.233***
	(0.026)	(0.052)	(0.027)	(0.055)	(0.026)	(0.053)	(0.027)	(0.055)	(0.026)	(0.053)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	42,377	42,377	38,820	38,820	41,611	41,611	38,732	38,732	41,820	41,820
Adj-R2	0.074	0.120	0.080	0.126	0.074	0.121	0.074	0.121	0.074	0.120

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Each sub-sector is dropped in turn and the model is re-estimated. For the correspondence between the sub-sector omitted and the label used in the table, see Table 2. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A16: β-convergence estimates for labour productivity in manufacturing sub-sectors, leave-one-out test by regions.

	Full Sample		W/O AAS		W/O LAM		W/O EAS		W/O ENA	
	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Initial value (L1)	-0.024***	-0.098***	-0.025***	-0.103***	-0.017***	-0.087***	-0.026***	-0.099***	-0.031***	-0.100***
	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)	(0.006)	(0.004)	(0.006)
×Post-1990s	-0.040***	-0.031***	-0.043***	-0.031***	-0.039***	-0.028***	-0.040***	-0.035***	-0.043***	-0.032***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Constant	0.539***	1.230***	0.566***	1.274***	0.455***	1.097***	0.573***	1.290***	0.621***	1.227***
	(0.026)	(0.052)	(0.028)	(0.056)	(0.022)	(0.052)	(0.030)	(0.062)	(0.035)	(0.061)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	42,377	42,377	39,071	39,071	37,535	37,535	34,724	34,724	28,692	28,692
Adj-R2	0.074	0.120	0.077	0.125	0.075	0.119	0.081	0.127	0.076	0.119

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Each region is dropped in turn and the model is re-estimated. For the correspondence between the country and the region omitted, see Table A4. The abbreviations are defined as follows: AAS denotes Advanced Asia and Oceania, LAM Latin America, EAS Emerging Asia and Oceania, and ENA Europe and North America. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A17: β-convergence estimates for labour productivity in manufacturing sub-sectors, leave-one-out test by regions.

	Full Sample		W/O MENA		W/O PSS		W/O SSA		W/O WIOI	
	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.	Uncond.	Cond.
Initial value (L1)	-0.024***	-0.098***	-0.027***	-0.099***	-0.024***	-0.098***	-0.025***	-0.098***	-0.024***	-0.097***
	(0.003)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.003)	(0.005)	(0.003)	(0.005)
×Post-1990s	-0.040***	-0.031***	-0.038***	-0.033***	-0.037***	-0.032***	-0.039***	-0.030***	-0.040***	-0.033***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.539***	1.230***	0.558***	1.261***	0.504***	1.224***	0.551***	1.239***	0.541***	1.235***
	(0.026)	(0.052)	(0.027)	(0.059)	(0.027)	(0.052)	(0.027)	(0.055)	(0.026)	(0.053)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	42,377	42,377	37,855	37,855	38,309	38,309	38,820	38,820	41,611	41,611
Adj-R2	0.074	0.120	0.080	0.127	0.070	0.116	0.080	0.126	0.074	0.121

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). Each region is dropped in turn and the model is re-estimated. For the correspondence between the country and the region omitted, see Table Table A4. The abbreviations are defined as follows: MENA denotes Middle East and North Africa, PSS Post-Soviet States, SSA Sub-Saharan Africa, and WIOI West Indies and Other Islands. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A18: β-convergence estimates for labour productivity in manufacturing sub-sectors, STiM robustness test

	Unconditional Convergence					Conditional Convergence				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Initial value (L1)	-0.052***	-0.023***	-0.012***	-0.045***	-0.045***	-0.116***	-0.091***	-0.085***	-0.117***	-0.123***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)
×Post-1990s		-0.041***					-0.034***			
		(0.004)					(0.004)			
×1970*s*			-0.010**					-0.009*		
			(0.005)					(0.005)		
×1980*s*			-0.016***					-0.003		
			(0.006)					(0.005)		
×1990*s*			-0.080***					-0.051***		
			(0.007)					(0.006)		
×2000*s*			-0.043***					-0.031***		
			(0.005)					(0.006)		
×2010*s*			-0.028***					-0.027***		
			(0.007)					(0.008)		
×Mid-tech				-0.012**	-0.009				0.002	-0.011**
				(0.006)	(0.006)				(0.005)	(0.005)
×High-tech				-0.009	-0.009				0.002	0.003
				(0.006)	(0.006)				(0.005)	(0.005)
Constant	0.564***	0.541***	0.506***	0.564***	0.543***	1.210***	1.183***	1.153***	1.211***	1.295***
	(0.027)	(0.025)	(0.024)	(0.027)	(0.026)	(0.053)	(0.052)	(0.052)	(0.052)	(0.050)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Observations	39,254	39,254	39,254	39,254	36,271	39,254	39,254	39,254	39,254	36,271
Adj-R2	0.074	0.079	0.083	0.075	0.075	0.121	0.124	0.125	0.121	0.132

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). We drop observations. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A19: Conditional β-convergence estimates for labour productivity in manufacturing sub-sectors, per regions

	Full Sample		Only AAS		Only LAM		Only EAS		Only ENA	
	(6)	(9)	(6)	(9)	(6)	(9)	(6)	(9)	(6)	(9)
Initial value (L1)	-0.091***	-0.117***	-0.049***	-0.063***	-0.135***	-0.189***	-0.092***	-0.116***	-0.094***	-0.120***
	(0.005)	(0.005)	(0.010)	(0.020)	(0.017)	(0.029)	(0.011)	(0.013)	(0.009)	(0.010)
×Post-1990s	-0.034***		-0.035**		-0.106***		-0.018		-0.030***	
	(0.004)		(0.013)		(0.027)		(0.011)		(0.008)	
×Mid-tech		0.002		-0.001		-0.025		0.025*		0.002
		(0.005)		(0.021)		(0.035)		(0.014)		(0.009)
×High-tech		0.002		-0.009		-0.004		-0.007		0.004
		(0.005)		(0.019)		(0.040)		(0.016)		(0.010)
Constant	1.183***	1.211***	0.802***	0.763***	2.119***	2.097***	1.011***	1.065***	1.234***	1.300***
	(0.052)	(0.052)	(0.120)	(0.111)	(0.178)	(0.180)	(0.093)	(0.087)	(0.093)	(0.095)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,254	39,254	3,256	3,256	4,816	4,816	7,649	7,649	13,663	13,663
Adj-R2	0.124	0.121	0.254	0.252	0.246	0.239	0.173	0.174	0.210	0.209

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). For the correspondence between the country and the region omitted, see Table A4. The abbreviations are defined as follows: AAS denotes Advanced Asia and Oceania, LAM Latin America, EAS Emerging Asia and Oceania, and ENA Europe and North America. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. The unconditional convergence setting of this Table is available in the Appendix, Table 7. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A20: Conditional β-convergence estimates for labour productivity in manufacturing sub-sectors, per regions

	Full Sample		Only MENA		Only SSA		Only WIOI	
	(6)	(9)	(6)	(9)	(6)	(9)	(6)	(9)
Initial value (L1)	-0.098***	-0.121***	-0.098***	-0.109***	-0.067***	-0.119***	-0.197***	-0.060*
	(0.005)	(0.005)	(0.010)	(0.013)	(0.018)	(0.018)	(0.048)	(0.033)
×Post-1990s	-0.031***		-0.031***		-0.088***		0.150***	
	(0.004)		(0.009)		(0.019)		(0.038)	
×Mid-tech		0.001		-0.017		-0.002		-0.030
		(0.005)		(0.012)		(0.022)		(0.026)
×High-tech		-0.001		-0.007		0.003		0.066**
		(0.006)		(0.012)		(0.046)		(0.031)
Constant	1.230***	1.256***	1.186***	1.176***	1.126***	1.128***	0.846**	0.513*
	(0.052)	(0.053)	(0.114)	(0.109)	(0.171)	(0.166)	(0.325)	(0.282)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year X Indus. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,377	42,377	4,520	4,520	3,543	3,543	567	567
Adj-R2	0.120	0.118	0.187	0.185	0.242	0.234	0.515	0.515

Notes: As stated in the core of the paper, this table reports β-convergence estimates as understood as the negative relationship between the initial level of labour productivity and its subsequent annual growth rate ($T = 1$). For the correspondence between the country and the region omitted, see Table A4. The abbreviations are defined as follows: MENA denotes Middle East and North Africa, PSS Post-Soviet States, SSA Sub-Saharan Africa, and WIOI West Indies and Other Islands. To facilitate interpretation, the first two columns report the baseline estimates for the full sample, as shown in Table 3. The unconditional convergence setting of this Table is available in the Appendix, Table 7. Robust standard errors clustered at the country-manufacturing sub-sector level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.