Unconditional Convergence in Manufacturing: A Reassessment

By Berthold Herrendorf, Richard Rogerson and Ákos Valentinyi*

The movement of labor out of the agricultural sector is a central feature of the development process. A long-held belief is that successful development requires that much of the labor released from agriculture be allocated to manufacturing rather than services. Rodrik's (2013) finding of unconditional convergence for manufacturing productivity using data from UNIDO provided empirical support for this view. We argue that the UNIDO data are ill–suited to study cross-country productivity dynamics. We use recently released data from the GGDC that was developed especially to study cross-country sectoral productivity dynamics to revisit this issue. We find no evidence of unconditional convergence in manufacturing productivity over the period 1990–2018.
JEL: O47; Q10
Keywords: convergence; manufacturing; development

I. Introduction

A salient feature of the development process is the large-scale movement of labor out of agriculture. The share of workers employed in agriculture in today's advanced economies has decreased from roughly 70 percent in 1800 to less than 5 percent today, and today's developing economies are in the midst of this same process. An important issue is whether development success depends on where the labor released from agriculture is allocated. Specifically, does it matter how this labor is allocated between manufacturing and services? The answer to this question is intimately related to the issue of whether the phenomenon of "premature deindustrialization" (Rodrik (2016) and Felipe et al (2019)) has negative consequences for development.

* Herrendorf: Arizona State University, Department of Economics, W.P. Carey School of Business 350 East Lemon Street, Tempe, AZ 85287-3806, USA, Berthold.Herrendorf@asu.edu. Rogerson: Princeton University and NBER, Woodrow Wilson School Princeton University Princeton NJ 08544, rdr@Princeton.edu. Ákos Valentinyi: University of Manchester, CEPR, Corvinus University Budapest, Department of Economics, Arthur Lewis Building, Oxford Road, Manchester M13 9PL, United Kingdom, valentinyi.a@gmail.com. This paper replaces our earlier paper entitled "New Evidence on Sectoral Labor Productivity: Implications for Industrialization and Development". We have received helpful comments and suggestions from Gaaitzen de Vries, Douglas Gollin, Robert Inklaar, Joseph Kaboski, Dani Rodrik, Marcel Timmer and the presentations participants at ASU, Autonoma de Barcelona, the CEPR STEG Conference, the CEPR European Summer Symposium in International Macroeconomics, Corvinus University Budapest, the LAEF Growth, Development and Structural Transformation Conference at USBC, the NBER Summer Institute, Manchester, the University of Pennsylvania, the SED Conference and Swansea University. Valentinyi thanks the Hungarian National Research, Development and Innovation Office (Project KJS K 124808). We are responsible for all errors and omissions.

A long-standing belief is that successful development requires much of the labor released from agriculture during the early stages of the development process to be allocated to manufacturing rather than services.[1] Kaldor (1967) enshrined this belief as the First Law of Growth, based on the notion that the manufacturing sector featured both high productivity and high productivity growth.[2] This notion gives rise to two channels through which higher employment in manufacturing promotes aggregate productivity growth: a high level of productivity in manufacturing represents a static channel, while a high growth rate of productivity in manufacturing represents a dynamic channel. But what is the reality of sectoral productivity dynamics in developing economies? And does it support a special role for manufacturing employment in the early stages of development?

Evidence that speaks directly to these questions has been scarce. One important exception is Rodrik (2013). He presented evidence of relatively strong unconditional convergence of manufacturing labor productivity for a broad sample of countries that included many developing economies. If manufacturing productivity exhibits unconditional convergence, then a high employment share in manufacturing will facilitate convergence at the aggregate level via the dynamic channel mentioned above. Consistent with this, Rodrik concluded "...aggregate convergence fails due to the small share of manufacturing employment in low-income countries and the slow pace of industrialization."

Rodrik's analysis of manufacturing labor productivity dynamics was based on data from UNIDO (INDSTAT Rev2). In this paper, we argue that the limitations of the UNIDO data make it ill-suited for productivity comparisons.[3] Newly available data from the Groningen Growth and Development Center (GGDC) allows us to create comparable measures of sectoral productivity for a broad sample of countries for the period 1990-2018. We use this data to investigate both the level and changes in sectoral labor productivity gaps for agriculture, manufacturing and market services.[4] This dataset possesses three key features: (i) data collection is harmonized across countries and over time (ii) it is comprehensive in measuring all activity within each sector, including self-employment and informal activity (iii) it includes PPPs that allow one to reliably compare sectoral labor productivity levels across countries.

Our analysis yields three main findings. First, 1990-2018 features a modest amount of unconditional convergence in aggregate labor productivity.[5] Second,

[1] In its 2018 World Economic Outlook, the IMF wrote "The declining share of manufacturing jobs in overall employment has been a concern for policy makers and the broader public....The concern stems from the widely held belief that manufacturing plays a unique role as a catalyst for productivity growth and income convergence....". Felipe et al (2019) note that emerging market economies often target manufacturing activity as part of their development initiatives, and specifically mention initiatives in China, India, Indonesia and the Philippines. Brazil's Nova Industria Brasil is another recent example.

[2] The idea that high and growing productivity are unique features of manufacturing dates back at least to Smith (1776). But see, for example, the sharp criticism of Kaldor's views in Bhagwati (2010).

[3] Additionally, because the UNIDO data only covers manufacturing it cannot address whether there is something special about manufacturing.

[4] Market services is the composite of wholesale, retail, transport, business, financial and other services.

[5] This finding mirrors those in Patel et al. (2021) and Kremer et al. (2022)

the dynamic channel favors market services over manufacturing. Specifically, we find no evidence for unconditional convergence in manufacturing productivity, and evidence of modest unconditional convergence in market services productivity. We also find modest unconditional convergence in agricultural productivity. Our third finding concerns sectoral productivity gaps between rich and poor economies, and thus reflects the static channel. In 1990, productivity gaps in manufacturing and market services were roughly equal and smaller than aggregate productivity gaps, while agricultural productivity gaps were larger than aggregate productivity gaps. As of 2018, productivity gaps in market services are smaller than productivity gaps in manufacturing.

Why do our conclusions differ from those in Rodrik (2013)? Because convergence properties may be specific to certain countries and time periods, one possibility is that the different findings reflect the result of differences in time periods and samples of countries. But we show that the starkly different results continue to hold if we limit attention to the overlapping sample of 48 countries for the time period 1995-2005.

We argue that a key reason for the different results is differences in coverage. Whereas the GGDC seeks to provide a comprehensive measure of value added and employment that takes into account the importance of self-employment and informal enterprises in poor countries, the UNIDO data are based on surveys that restrict coverage based on firm size thresholds and whether firms are officially registered. Acknowledging this, the last sentence of Rodrik's abstract asserts that the finding of unconditional convergence should *"....be viewed as applying to the organized and formal parts of manufacturing"*.

Recent research on informality strongly cautions against the validity of this interpretation. As highlighted by Ulyssea (2018), informal workers constitute a large share of employment in formal sector firms in developing countries. Precisely because formal firms hire informal workers in order to avoid payroll taxes and regulation, it is highly likely that formal firms do not include informal workers when responding to surveys. It follows that reported employment may significantly understate actual employment, thus rendering measures of labor productivity unreliable. Because informality varies across countries, cross-country productivity comparisons based on the UNIDO data are not reliable, and changes in informality over time makes measures of productivity growth rates unreliable.

We use the GGDC data to construct a measure of coverage for manufacturing employment in the UNIDO data. This measure displays a strong positive correlation with ILO measures of formality for the manufacturing sector. Decreases in coverage are systematically associated with higher labor productivity growth in the UNIDO data, thus raising the concern that measurement issues affect the conclusion of unconditional convergence. In fact, the finding of unconditional convergence disappears if one removes countries with large decreases in coverage.

Our paper relates to a recent literature that studies convergence from a sectoral perspective. Like us, Dieppe and Matsuoka (2025) and Kinfemichael and Morshed

(2019) study sectoral productivity dynamics for a large sample of developing and advanced economies. A key limitation of their analyses is that they do not have sectoral PPPs and instead assume that the law of one price holds for all sectors. Inklaar and Marapin (2025) use the same data as us to provide a structural change perspective on aggregate productivity convergence. Diao et al. (2019) studies aggregate productivity dynamics from a structural change perspective but does not compare sectoral productivity across countries. Our finding that selection effects have a large effect on measured productivity is consistent with the analysis in Diao et al. (2024). They study manufacturing productivity dynamics in Ethiopia and Tanzania and highlight the different dynamics of large and small firms.

II. Data And Measurement

In this section we briefly describe the data used to construct sectoral labor productivity for a broad sample of 68 countries over the period 1990-2018.

A. *The Economic Transformation Database*

The Economic Transformation Database (ETD) is a panel of 51 mostly poor countries in Asia, Africa, and Latin America, covering the period 1990–2018, and administered by the Groningen Growth and Development Center (GGDC). It contains information on employment (persons engaged), sectoral nominal value added, and sector value added in 2015 (domestic) prices for 12 sectors. In what follows, we focus on agriculture, manufacturing, and a composite sector that we refer to as market services, consisting of wholesale and retail trade, transportation, business services, finance, and other services. We exclude two services sectors: real estate and government, as the output of these sectors is largely imputed.[6] Including these categories in our measure of services does not affect any of our findings.

The ETD is heavily skewed toward poor countries; in 1990 more than 40% of the countries had GDP/worker less than 10% of the US level, roughly 60% had GDP/worker less than 20% of the US value, and only one was higher than 75% of the US value.[7] The large representation of poor countries makes the ETD attractive for studying productivity patterns in developing economies.

The ETD also features substantial heterogeneity in aggregate productivity growth experiences. The distribution of average annual productivity growth rates features 19 countries below 2%, 27 between 2 and 4 percent, and 5 above 4%. This heterogeneity remains large even if we focus on the 31 poorest countries, with almost an even split between those growing faster and slower than 3% per year.[8]

[6] The label of "government" in these data is somewhat misleading, as it includes education and health independently of whether they are publicly provided.

[7] Table A1 in the Appendix reports the distribution of GDP/worker relative to the US.

[8] Table A2 in the Appendix provides more detail on the distribution of growth rates.

B. Construction of the ETD

This subsection provides more detail on the data collection underpinning the ETD.[9] Data collection poses many challenges, especially in less developed countries. These challenges notwithstanding, the Penn World Table (PWT) is a standard source for comparisons of aggregate labor productivity across countries. The ETD and the PWT are both administered by the GGDC and the ETD is based on the same underlying data used to construct the PWT. The ETD essentially represents a disaggregated version of the PWT data on employment and output-side real GDP. In the Online Appendix we compare aggregate labor productivity levels as reported in the ETD and the PWT. A log-linear regression yields an R-squared of .99

On the output side, and like the PWT, the ETD relies on official national accounts data for value added in both current and constant prices. Countries' national accounts follow the international System of National Accounts (SNA) framework, which provides a coherent and consistent set of definitions and accounting rules across countries. Importantly, national accounts aim to capture the entire production boundary, including informal economic activity, so using them ensures broad coverage and comparability of the data.[10] The sectoral breakdown of ETD data follows the International Standard Industrial Classification (ISIC) of economic activities, which is the internationally agreed-upon reference classification used in national accounts, enterprise registers, labor surveys, and other statistics.

On the employment side, and again like the PWT, the ETD constructs employment series using decennial population censuses and annual labor force and other surveys. Decennial population censuses are used to estimate sectoral employment levels in reference years, and growth rates from annual labor force and other surveys are applied to estimate employment levels in non-reference years. Population censuses are preferred to establishment surveys because of their more complete coverage of the population, specifically of self-employed and informal workers. Labor force surveys are sometimes skewed toward activity in urban areas. The use of population censuses to target levels distinguishes the GGDC data from the data reported by the ILO, which relies only on labor force surveys.[11] Because both the labor statistics and the national accounts use ISIC classifications, sectoral employment figures are conceptually consistent with the sectoral value added data, and comparable across countries.

Sectoral value added data is also available from the World Development In-

[9]See Kruse et al. (2022) for a short and de Vries et al. (2021) for a long and detailed description of the general methodology for how the ETD is constructed and how it is implemented for each country in the ETD.

[10]See OECD (2002) for more details about the measurement of the informal economy in national accounts data.

[11]Another distinction between ILO and ETD measures of employment is that as of 2013, the ILO no longer counts individuals producing for their own use as employed. This mostly affects subsistence farmering and so is not of first order importance for measures of manufacturing employment.

dicators, and sectoral employment data is also available from the International Labor Organization (ILO).[12] WDI measures of value added are based on the same underlying national accounts data used by both the PWT and the ETD, and as noted earlier, ILO employment measures are based on labor force surveys.

Given our interest in productivity measures, we prefer to use value added and employment data from a common source in order to maximize harmonization. An additional argument in support of using the ETD measures is that the sectoral PPP measures that we take from the PLD2023 (described below) use sectoral value added measures from the ETD as an input in their construction. Nonetheless, in the Online Appendix, we show that manufacturing productivity measures generated by different combinations of value added and employment measures are very highly correlated. Log-linear regressions yield R-squareds in the range of 0.96 to 0.98. Moreover, our conclusions regarding unconditional convergence of manufacturing productivity are also robust to using these alternative measures.

C. *Expanding the ETD*

To have greater representation of countries close to the aggregate productivity frontier, we expand the ETD sample by adding four western offshoots (Australia, Canada, New Zealand, and the US), fifteen western European countries (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Spain, Sweden, and the UK), and Russia. The primary data source for the western offshoots is national accounts and employment data from the OECD. Data for the western European countries are from Eurostat. In the case of missing data, we used growth rates from EUKLEMS, WORLD KLEMS or data from National Statistical Agencies to extrapolate the last available observation. Data for Russia are from the GGDC (see Hamilton and de Vries (2025)). This expansion of the ETD is built around the national accounts from the OECD and Eurostat to ensure comprehensiveness, consistency, and comparability across countries.

D. *The Productivity Level Data Base*

One important limitation of the ETD is that it does not include sectoral PPPs that are needed to create comparable measures of sectoral productivity across countries. For this, we turn to the 2023 edition of the Productivity Level Database (henceforth PLD2023), also maintained by the GGDC. This data set provides sectoral PPPs for the same 12 sectors in the ETD for a sample of 84 countries in three benchmark years: 2005, 2011, and 2017.[13] PPPs are normalized such that PPPs for the US for each year and sector are equal to 1. We emphasize that

[12]The WDI does not generate its own sectoral employment data and the ILO does not generate sectoral value added data.

[13]The underlying data come from the International Comparisons Project (ICP). See Inklaar et al. (2024) for a detailed description of this data set and the underlying methodology. It is important to note that the methodology for constructing these PPPs uses nominal sector value added data from the ETD as an input, thereby linking the ETD and the PLD2023.

whereas the WDI and ILO provide alternative sources for sectoral employment and value added in domestic units, neither of them provides measures of sectoral PPPs.

All but three of the countries in our expanded ETD sample are contained in the PLD: Burkina Faso, Lesotho, and Mozambique. In what follows, we focus on the 68 countries that appear in both, and with some abuse of terminology, refer to this sample as the Expanded Economic Transformation Database (EETD). For completeness, the list of countries of the EETD is in Appendix (A.1).

The EETD maintains the advantages of the ETD while considerably expanding coverage. As of 2018, the EETD represented more than 85% of the world's population and more than 88% of the world's GDP at current PPP in 2018 (calculated from PWT 10.01). It includes the 15 most populous and the 15 largest economies.

E. *Extending Productivity Measures to Non-Benchmark Years*

To construct time series for sectoral value added in PPP covering the entire 1990-2018 period, we follow a variant of the method used in the construction of PWT data since version 8.0. Specifically, assuming a single benchmark year t_1 for which we have sectoral PPPs, we extrapolate the sectoral PPP for sector i in country j to year t using the formula

$$PPP_{i,j,t} = PPP_{i,j,t_1} \frac{P_{i,j,t}/P_{i,j,t_1}}{P_{i,USA,t}/P_{i,USA,t_1}} \tag{1}$$

where $P_{i,j,t}$ is the price index for sector i in country j in period t. Since PPPs for the benchmark year are normalized relative to the US, this procedure effectively extrapolates using a measure of sectoral inflation relative to the United States.

If there are multiple benchmark years with PPPs, the results of this procedure for a given year will potentially vary with the choice of a benchmark year. To deal with this issue, we proceed as follows. For years prior to the earliest benchmark, we extrapolate backward using data from the earliest benchmark year, and for years subsequent to the latest benchmark, we extrapolate forward using data from the latest benchmark year. For a year $t \in [t_1, t_2]$ that lies between two consecutive benchmark years, t_1 and t_2, we use the geometric average of the PPPs extrapolated from the two benchmark years to construct a smooth time series of PPPs

$$PPP_{i,j,t} = \left(PPP_{i,j,t_1} \frac{P_{i,j,t}/P_{i,j,t_1}}{P_{i,USA,t}/P_{i,USA,t_1}} \right)^{1-w_t} \left(PPP_{i,j,t_2} \frac{P_{i,j,t}/P_{i,j,t_2}}{P_{i,USA,t}/P_{i,USA,t_2}} \right)^{w_t} \quad \forall t \in [t_1, t_2] \tag{2}$$

where $w_t \equiv (t - t_1)/(t_2 - t_1)$.[14]

[14]Differently than the PWT, which uses the arithmetic average, we use the geometric formula following the recommendation of Rao, Inklaar and Rambaldi 2018, as it preserves transitivity of the PPPs.

We also use these data to construct measures of aggregate productivity. The PLD2023 is based on the PPP construction method developed in Inklaar and Diewert (2016) and we follow their procedure to construct aggregate PPPs. Specifically, we aggregate the sector PPPs for each of the three benchmark years in 2005, 2011 and 2017, and then extrapolate these PPPs the same way as we extrapolated the sector PPPs, and normalize them to the US level in each year. This method ensures that the value added in current PPPs is equal to the current dollar prices for the United States.

III. Results

In this section we document properties of labor productivity across countries at the aggregate and sectoral level in order to assess the static and dynamic channels noted in the introduction.

A. *Productivity Convergence: The Dynamic Channel*

We begin with an analysis of the convergence properties of aggregate and sectoral labor productivity.

We focus on β-convergence, i.e., the tendency for countries with lower initial levels of productivity to have higher productivity growth rates.[15] The standard approach for assessing β-convergence is to regress the change in log productivity on the initial level of log productivity:[16]

$$\Delta \log(LP_{jt}) = \alpha + \beta \log(LP_{jt-1}) + D_t + \varepsilon_{jt}, \tag{3}$$

where the D_t are time fixed effects and LP_{jt} is a PPP measure of labor productivity (at either the sectoral or aggregate level) in country j and period t. If β is negative, there is a tendency for low productivity countries to catch up to high productivity countries.

The results presented in Panel I of Table 1 indicate no evidence of unconditional convergence for manufacturing productivity and a statistically significant though economically very modest degree of unconditional convergence for each of aggregate, agricultural, and market services productivity. Our finding of statistically significant unconditional convergence at the aggregate level is consistent with the findings of Patel et al (2021) and Kremer et al. (2022).[17] The magnitude of this estimated effect is very modest: the point estimate of -0.0076 implies that a country at 0.1 of the frontier in 1990 will only be at 0.156 of the frontier in 2018.[18] The coefficients for agriculture and market services are even smaller in absolute value.

[15] An alternative is σ-convergence, which refers to a tendency for cross-sectional dispersion to decrease over time. Results for σ-convergence are in online Appendix A.3.2.

[16] See Barro and Sala-i-Martin (2003) for a discussion of convergence regressions.

[17] Sample and time period vary across these studies. Our point estimate is closer to that of Kremer et al. (2022) but the key point is that all three imply a very modest degree of unconditional convergence.

[18] To obtain this number, subtract (3) for frontier productivity from (3) and take the exponential

Table 1—Convergence Regressions

Panel I.	**68 countries in EETD, 1990–2018**			
	Aggregate	Agriculture	Manufacturing	Market sevices
β	−0.0076	−0.0036	−0.0015	−0.0059
$p-$value	{0.0000}	{0.0029}	{0.6638}	{0.0044}
Number of observations	1,904	1,904	1,904	1,904
Units	PPP	PPP	PPP	PPP
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No

Panel II.	**48 countries in EETD ∩ UNIDO, 1995–2005**		
		Manufacturing	
	EETD (1)	EETD (2)	UNIDO (3)
β	0.0100	0.0087	−0.0178
$p-$value	{0.0486}	{0.0640}	{0.0023}
Number of observations	480	480	480
Units	PPP	USD	USD
Time fixed effects	Yes	Yes	Yes
Country fixed effects	No	No	No

The Online Appendix reports two sensitivity exercises. First, we rerun these regressions but leaving out one of the following groups each time: Sub-Saharan Africa, South and East Asia, Latin America, and North Africa, the Middle East, and Central Asia. Second, we examine how the results for the manufacturing sector are affected by using WDI measures of manufacturing value added and ILO measures of manufacturing employment. In all cases we find no evidence of unconditional convergence for manufacturing.

B. Productivity Gaps: The Static Channel

Several papers have documented that less developed economies have larger productivity gaps in agriculture than in the aggregate.[19] The implication is that reallocating labor from agriculture to non-agriculture will reduce aggregate pro-

function:

$$\frac{LP_{t+28}}{LP^{\text{Front.}}_{t+28}} = \exp\left((1+\beta)^{28}\log\left(\frac{LP_t}{LP^{\text{Front.}}_t}\right)\right) = 0.1^{(1+\beta)^{28}} \approx 0.159$$

[19]Restuccia et al. (2008) and Caselli (2005) document this using FAO data.

ductivity gaps. If productivity gaps vary within the non-agricultural sector then this effect will depend on how workers are allocated within the non-agricultural sector.

To explore this we compare sectoral and aggregate productivity gaps for agriculture, manufacturing and market services. Though previous research has documented the relationship between agricultural and aggregate productivity gaps using FAO data, we include it here both for completeness and because the FAO data stops in 1985.

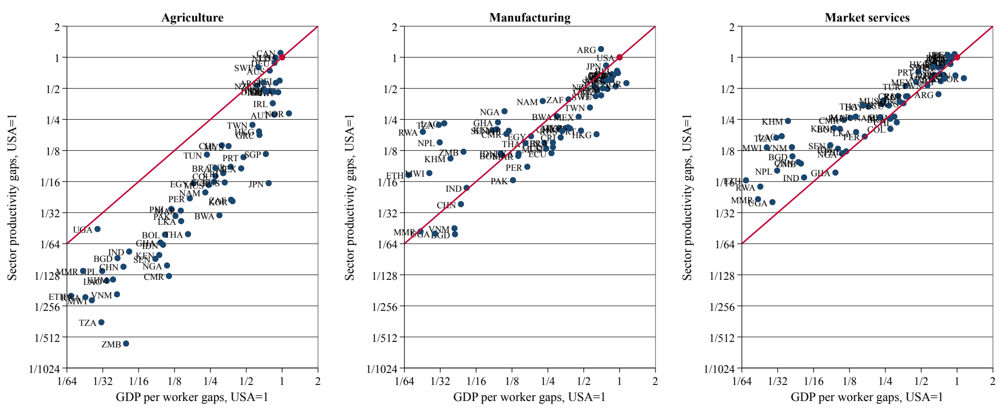


Figure 1. Sector Productivity Gaps in 1990

Results for 1990 are shown in Figure 1. We highlight two messages. First, focusing on less developed economies, productivity gaps in agriculture are larger than aggregate productivity gaps, whereas gaps in both manufacturing and market services are smaller than aggregate productivity gaps. Second, the relative gaps in manufacturing and market services are essentially uncorrelated with aggregate productivity gaps. Specifically, the correlation of the log of the manufacturing productivity gap less the log of the market services productivity gap with the log of the aggregate productivity gap is essentially zero, equal to -0.084.[20]

C. Manufacturing Employment and Aggregate Productivity Growth

Rodrik (2013) argued that unconditional convergence in manufacturing did not translate into convergence at the aggregate level because low-income countries either had too little employment in manufacturing or failed to expand employment in manufacturing. Although we find no evidence for unconditional convergence, it is possible that manufacturing employment is related to aggregate productivity growth. We examine this possibility using the EETD data.

[20]Consistent with our earlier finding of unconditional convergence in market services but not in manufacturing, this correlation increases over time, rising to 0.085 in 2005 and 0.398 in 2018. As of 2018, productivity gaps in manufacturing exceed those in market services for less developed countries.

To focus on countries in the early stage of development, we study the 31 countries in the EETD with GDP per worker in 1990 less than 20 percent of the US level. We previously noted that this sample displays substantial heterogeneity in aggregate productivity growth. Importantly, it also displays substantial variation in the manufacturing employment share in 1990. Even excluding China, which is an outlier at the high end with a value above .20, the manufacturing employment share in 1990 ranges from 0.02 to 0.15. There is also substantial variation in the change in the manufacturing employment share, ranging from -0.05 to $+0.10$.

Considering changes over the entire 1990-2018 period, the correlation between aggregate labor productivity growth and the 1990 manufacturing employment share is -0.01, and the correlation between aggregate labor productivity growth and the change in the manufacturing employment share is -0.14. Neither is significantly different from zero.

D. Summary

Three key messages emerge from our analysis. First, consistent with the existing literature, there are large static productivity gains associated with moving labor out of agriculture. Second, as of 1990 the magnitude of this static effect was not dependent on whether workers were moved into manufacturing or market services, while as of 2018 it is larger when moving workers into market services. Third, dynamic gains are larger for market services than manufacturing.

IV. The Roles of Productivity Measures, Country Sample and Time Period

Our results for convergence in manufacturing productivity differ markedly from those in Rodrik (2013). This section examines some potential sources of these differences: the method used to make productivity comparisons across countries, and the role of time period and country sample.

A. The Role of Productivity Measurement

Rodrik did not have access to PPPs for manufacturing. Faced with this constraint, he used exchange rates to convert each country's manufacturing value added per worker in domestic currency into US dollars (USD), implicitly assuming that the law of one price holds to good approximation for the global manufacturing sector.

The PLD2023 allows us to compare PPP and USD measures of relative manufacturing productivity for the three benchmark years in the PLD2023. Appendix A.3.3 documents statistically significant departures from the law of one price in each of the three benchmark years. To assess the significance of this for convergence properties, we construct manufacturing productivity for our sample of 68 countries over the 1990-2018 period using the same procedure as Rodrik and repeat our analysis of β convergence. [21]

We find no evidence for economically meaningful unconditional convergence. The point estimate on lagged productivity is -0.0053 with a $p-$value of 0.0420.[22] Although the point estimate is statistically significant at the 5% level, it is small and very modest economically, implying that a country at 0.1 of the frontier in 1990 will only be at 0.137 of the frontier in 2018.[23]

We conclude that Rodrik's assumption that the law of one price holds does bias in favor of finding unconditional convergence, though this effect is not first order in terms of understanding the differences between his results and ours.

B. *The Role of Sample Properties*

Rodrik's analysis covered four ten-year periods starting in 1965 and ending in 2005, and considered samples of countries that varied over time depending upon data availability in UNIDO. Because convergence properties can vary over time and across samples of countries, differences in the sample of countries and time frame could explain the different results. To investigate this, we use the fact that the two studies overlap in terms of countries and time periods. This yields a sample of 48 countries for the time period 1995-2005. A list of the 48 countries is provided in Appendix A.1.

Results are reported in Panel II of Table 1.[24] The UNIDO data generate a point estimate that is both economically and statistically significant at the 5% level, though it is a bit smaller than the estimates in Rodrik (2013). His estimates were in the range of 2 to 3 percent per year, and his baseline specification produced an estimate of 2.9 percent per year. In stark contrast, the EETD data produce a coefficient with the opposite sign, indicating divergence rather than convergence, regardless of whether PPP or USD values are used. We conclude that the different results regarding unconditional convergence become even starker when we focus on a common set of countries and time period.

Panels (a) and (b) of Figure 2 display the convergence results diagrammatically. Convergence regression results are potentially affected by the measurement of both initial productivity levels and productivity growth rates, both of which may differ between the EETD and UNIDO. Panels (c) and (d) in Figure 2 show large differences in each of these measures between the two data sets. Productivity growth rates are only modestly correlated between the two datasets, with a correlation of 0.26. While the correlation in initial productivity levels for the overall sample is much higher, at 0.82, the correlation is much weaker in the

[21] Rodrik's procedure generates time series for productivity in current US dollars. Time fixed effects control for inflation in the US price level.

[22] A full set of results are contained in Table A9 in Appendix A.3.3.

[23] As noted earlier, Dieppe and Matsuoka (2024) estimated a convergence regression for the period 1995-2018 without having sectoral PPPs. They assumed that the law of one price holds and obtained a result similar to ours.

[24] When using the EETD data we calculate manufacturing labor productivity using both PPPs and Rodrik's method that relies on the law of one price. The results are essentially the same across these two specifications.

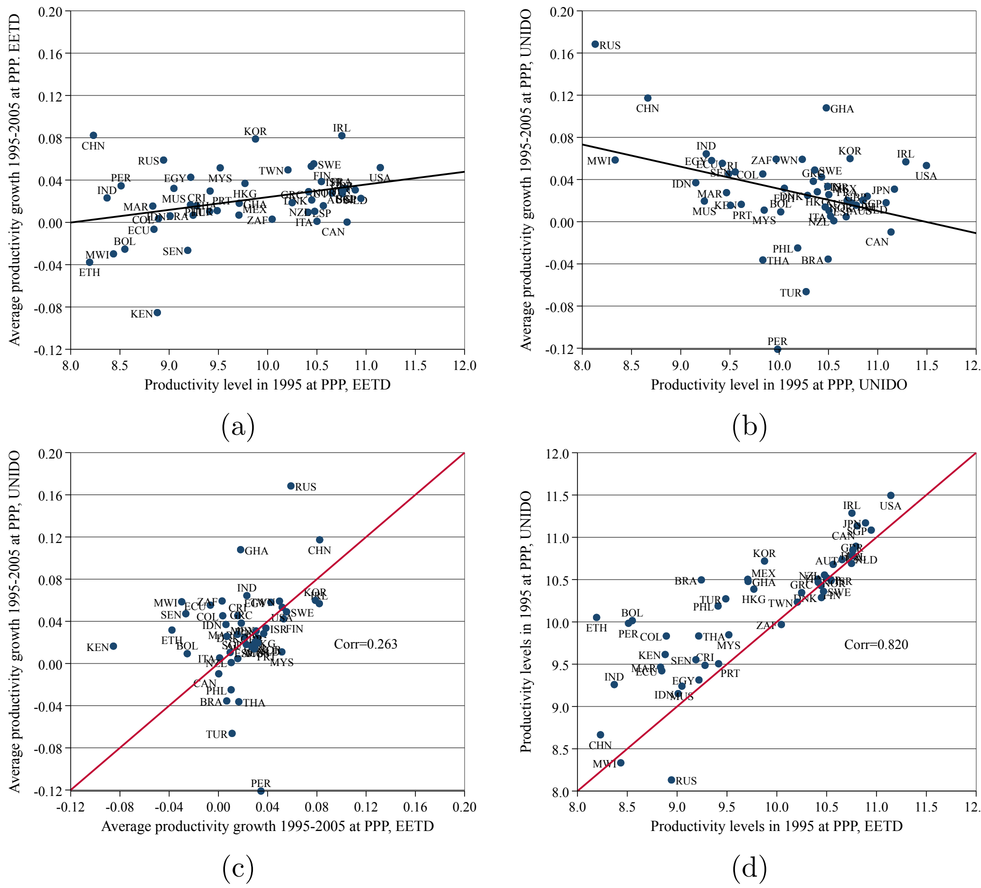


FIGURE 2. CONVERGENCE IN EETD AND UNIDO(48 countries in EETD ∩ UNIDO, 1995–2005)

lower part of the distribution. In particular, if we focus on the 21 countries with GDP/worker less than 20 percent of the US level in 1995 (PPP productivity below 9.534), the correlation between the two measures is only 0.34.

When we run the convergence regression using UNIDO data and substituting EETD measures for initial productivity levels or productivity growth, the estimate of β loses statistical significance.[25]

V. Differences in Coverage

Whereas the GGDC seeks to provide a comprehensive measure of value added and employment that takes into account the importance of self-employment and informal enterprises in poor countries, the UNIDO data are based on surveys that

[25] When using EETD values for the initial level the regression coefficient is -0.0058 with a $p-$value of 0.2537, and when we use EETD values for productivity growth the regression coefficient is 0.0088 with a $p-$value of 0.1615. In both cases we converted the EETD values into USD.

restrict coverage based on firm size thresholds and whether firms are officially registered. In this subsection, we study the role of differences in coverage.

A. Differences in Average Coverage Across Countries

The survey coverage of advanced economies tends to be very complete in the UNIDO data. To best focus on the set of poorer countries that are of greatest interest, we restrict attention to the overlapping sample of 30 countries in both UNIDO and the ETD for the period 1990–2018.[26]

For each year and country, we calculate the ratio of manufacturing employment in the UNIDO data to manufacturing employment in the GGDC data and refer to this ratio as *coverage ratio*.

More than 40% of the countries in this sample have average coverage ratios less than 50 percent, and three quarters of them have coverage less than 75 percent. Variation in coverage is large even for countries at similar levels of development. This raises the potential issue that selection of firms into the UNIDO surveys varies across countries, making cross-country comparisons unreliable.

B. Changes in Coverage Over Time Within Countries

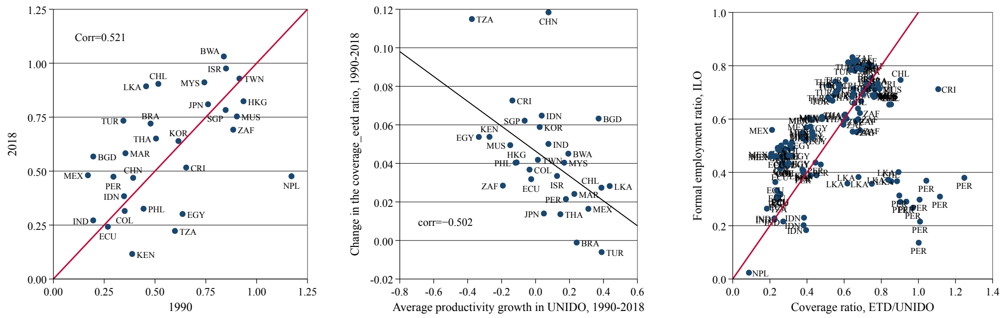
Many countries experience significant changes in the coverage ratio over time. Figure 3a shows a scatter plot of values in 1990 versus 2018. Although the points tend to follow the 45 degree line (the correlation is 0.52), there are large deviations, both up and down, for individual countries. To the extent that informal activity tends to decrease with development, one might have expected that most points in the figure would lie above the 45 degree line. From this perspective, the points below the 45 degree line are of potential concern.

This concern is validated when we examine the relationship between changes in coverage and productivity growth as measured in the UNIDO data. Figure 3b shows a systematic negative relationship between productivity growth in UNIDO and the change in our coverage ratio.[27]

The pattern in Figure 3b is consistent with two different mechanisms. One is that changes in coverage ratios are associated with changes in the use of informal workers in formal firms, a feature that we noted in the introduction. Decreasing (increasing) the share of informal workers leads to higher (lower) measured employment and lower (higher) productivity. Another possibility is that lower coverage reflects greater selection effects, with smaller and less productive firms being excluded. In both cases, productivity comparisons are not reliable.

[26]Some countries in the UNIDO dataset have missing observations for some years in the period 1990–2018. We include countries as long as they contain data for the majority of years and have observations at both the beginning and the end of the sample. We impute missing observations using linear interpolation.

[27]Nepal does not appear in this figure. It experienced a decrease in its coverage ratio of roughly 75 percentage points. Including it would require a scale that would obscure the overall pattern in the data. We also note that Nepal has a coverage ratio that exceeds one in 1990.



(a)
Coverage Ratios
1990 vs. 2018
30 countries
∈ EETD∩UNIDO

(b)
Changes in the Coverage Ratios
vs. Productivity Growth
30 countries
∈ EETD∩UNIDO

(c)
Coverage Ratio vs.
Formal Employment Rate
15 countries
∈ EETD∩UNIDO∩ILO

FIGURE 3. MANUFACTURING EMPLOYMENT COVERAGE RATIOS UNIDO–EETD

To examine the possibility that the convergence results in Rodrik (2013) might reflect inconsistent measurement due to changes in coverage, we repeat our earlier regression analysis using UNIDO data for our overlapping sample of 48 countries over the 1995-2005 period, but eliminating those countries that had decreases in their coverage rate that exceed some threshold. When this threshold is set to exclude all countries with a decline in their coverage ratio of at least 9 percentage points, the coefficient on lagged productivity loses statistical significance. This suggests that the evidence for unconditional convergence may well be spurious, driven by inconsistent data measurement.

C. *Coverage and Informality*

The ILO produces independent estimates of the informality rate in the manufacturing sector that are available in various years for several countries.[28] Panel (c) of Figure 3 shows a scatter plot of the coverage ratio defined earlier versus the ILO formality rate (i.e., 1−the informality rate) for the sample of 15 countries that appear in each of the EETD, UNIDO and the ILO datasets, with 161 individual country-year observations.[29]

Two messages emerge. First, with the exception of Peru and Sri Lanka, which we discuss in more detail below, there is a strong positive correlation between the ILO measure of formality and our coverage ratio. Second, the ILO formality measure tends to be higher than our coverage ratio. This is consistent with the UNIDO data not capturing all formal employment, possibly because some formal employment occurs at firms below the threshold used by the survey.

[28]These data are available at https://ilostat.ilo.org/topics/informality/.

[29]The countries are Bangladesh, Brazil, Chile, Colombia, Costa Rica, Ecuador, Egypt, Indonesia, India, Sri Lanka, Mexico, Mauritius, Nepal, Peru, South Africa, Thailand, and Turkey.

As mentioned above, the figure also indicates that Peru and Sri Lanka display extremely large and variable gaps between our coverage ratio and the formality measure from the ILO. These movements are driven by large and variable changes in UNIDO employment, suggesting that UNIDO measures may not be consistent over time within countries.[30]

VI. Conclusion

The early stages of development are associated with a large reallocation of labor out of the agricultural sector. Does it matter how this labor is allocated between manufacturing and services? Kaldor (1957) argued that it was important that this labor move into manufacturing rather than services. Rodrik (2013) offered evidence to support this conclusion: he found that manufacturing displays unconditional convergence, implying that a high employment share in manufacturing promotes overall productivity convergence.

Using recently released data from the GGDC, we build a new dataset of comparable labor productivity levels in manufacturing and market services for 68 countries during 1990–2018, including many less developed countries. We use this dataset to revisit the static and dynamic productivity gains associated with allocating agricultural labor to manufacturing rather than services. We find no evidence for unconditional convergence in manufacturing, and modest unconditional convergence in market services. In 1990 the static gains were similar for the two sectors, but as of 2018 are now larger for market services.

An interesting direction for future work is to use the newly available data on sectoral productivity to study aggregate productivity convergence from the perspective of structural change. Inklaar and Marapin (2025) takes a step in this direction.

Another important direction for future research is to study how the joint distribution of employment and productivity across establishments varies with development. We note two recent papers of interest. Bento and Restuccia (2017) build a structural model to understand how misallocation affects both the firm size distribution and productivity. And Diao et al. (2024) documents properties of the joint distribution of firm size and productivity in manufacturing in Ethiopia and Tanzania. The fact that many formal firms hire informal workers poses important challenges for this sort of work.

REFERENCES

Barro, Robert J. and Xavier Sala-i-Martin, *Economic Growth*, 2nd ed., New York: MIT Press, 2003.

[30] In the Online Appendix A1 we show that a comparison of the level of employment in UNIDO with the level of formal employment in the ILO data supports the same messages. This same message emerges when we study the relationship between changes in our coverage ratio and changes in the ILO formality rate.

Bento, Pedro and Diego Restuccia, "Misallocation, Establishment Size, and Productivity," *American Economic Journal: Macroeconomics*, 2017, *9*, 267–303. DOI:10.1257/mac.20150281.

Bhagwati, Jagdish, "The Manufacturing Fallacy," *Project Syndicate*, 27 Aug 2010. Available at: `https://www.project-syndicate.org/commentary/the-manufacturing-fallacy(Accessed:{January16th,2025})`.

Caselli, Francesco, "Accounting for Cross-Country Income Differences," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1A, Amsterdam and New York: North Holland, 2005, chapter 9, pp. 679–742. DOI:10.1016/S1574-0684(05)01009-9.

de Vries, Gaaitzen, Linda Arfelt, Dorothea Drees, Mareike Godemann, Calumn Hamilton, Bente Jessen-Thiesen, Ahmet Ihsan Kaya, Hagen Kruse, Emmanuel Mensah, and Pieter Woltjer, "The Economic Transformation Database (ETD): Content, Sources, and Methods," Technical Note, WIDER 2021. DOI:10.35188/UNU-WIDER/WTN/2021-2.

Diao, Xinshen, Margaret McMillan, and Dani Rodrik, "The Recent Growth Boom in Developing Economies: A Structural-Change Perspective," in Machiko Nissanke and José Antonio Ocampo, eds., *The Palgrave Handbook of Development Economics*, Cham: Palgrave Macmillan, 2019, chapter 9, pp. 281–334. DOI:10.1007/978-3-030-14000-7_9.

_ , Mia Ellis, Margaret S. McMillan, and Dani Rodrik, "Africa's Manufacturing Puzzle: Evidence from Tanzanian and Ethiopian Firms," *The World Bank Economic Review*, 2024, *39*, 308–340. DOI:10.1093/wber/lhae029.

Dieppe, Alistair and Hideaki Matsuoka, "Sectoral Decomposition of Convergence in Labor Productivity: A Re-examination from a New Dataset," *Empirical Economics*, 2025, *68*, 1829—-1859. DOI:10.1007/s00181-024-02692-y.

Hamilton, Calumn and Gaaitzen J. de Vries, "The Structural Transformation of Transition Economies," *World Development*, 2025, *191*, 106977. DOI:10.1016/j.worlddev.2025.106977.

Inklaar, Robert and Ryan Marapin, "Accounting for Productivity Convergence: the Role of Sectors and Structural Change," GGDC Research Memorandum 195, University of Groningen 2025. https://www.rug.nl/ggdc/productivity/pld/releases/pld-2023.

_ and W. Erwin Diewert, "Measuring Industry Productivity and Cross-Country Convergence," *Journal of Econometrics*, 2016, *191* (2), 426–433. DOI:10.1016/j.jeconom.2015.12.013.

_ , Ryan Marapin, and Kaira Gräler, "Tradability and Sectoral Productivity Differences across Countries," *IMF Economic Review*, 2024. DOI:10.1057/s41308-024-00271-w.

Kaldor, Nicholas, "A Model of Economic Growth," *Economic Journal*, 1957, *67*, 591–624. DOI:10.2307/2227704.

Kinfemichael, Bisrat and A.K.M. Mahbub Morshed, "Unconditional convergence of labor productivity in the service sector," *Journal of Macroeconomics*, 2019, *59*, 217–229. DOI:10.1016/j.jmacro.2018.12.005.

Kremer, Michael, Jack Willis, and Yang You, "Converging to Convergence," in Martin S. Eichenbaum and Erik Hurst, eds., *NBER Macroeconomic Annual*, Vol. 36, Cambridge, MA: MIT Press, 2022. DOI:10.1086/718672.

Kruse, Hagen, Emmanuel Mensah, Kunal Sen, and Gaaitzen de Vries, "A Manufacturing (Re)Naissance? Industrialization in the Developing World," *IMF Economic Review*, 2022, *63*. DOI:10.1057/s41308-022-00183-7.

OECD, *Measuring the Non-Observed Economy: A Handbook*, Paris: OECD, 2002. DOI:10.1787/9789264175358-en.

Patel, Dev, Justin Sandefur, and Arvind Subramanian, "The New Era of Unconditional Convergence," *Journal of Development Economics*, 2021, *152*, 102687. DOI:10.1016/j.jdeveco.2021.102687.

Rao, D.S. Prasada, Robert Inklaar, and Alicia Rambaldi, "Options for Producing "Smoothened" PPP Time–Series for the Years between Reference Year Comparisons," 2th Meeting of the International Comparison Program (ICP) Technical Advisory Group (TAG), World Bank 2018.

Restuccia, Diego, Dennis Tao Yang, and Xiaodong Zhu, "Agriculture and Aggregate Productivity: A Quantitative Cross–Country Analysis," *Journal of Monetary Economics*, 2008, *55*, 234–50. DOI:10.1016/j.jmoneco.2007.11.006.

Rodrik, Dani, "Unconditional Convergence in Manufacturing," *Quarterly Journal of Economics*, 2013, *128*, 165–204. DOI:10.1093/qje/qjs047.

_ , "Premature Deindustrialisation," *Journal of Economic Growth*, 2016, *21*, 1–33. DOI:10.1007/s10887-015-9122-3.

Smith, Adam, *Wealth of Nations* Wordsworth Classics of World Literature, Wordsworth Editions, [1776] 2012.

Ulyssea, Gabriel, "Firms, Informality, and Development: Theory and Evidence from Brazil," *American Economic Review*, 2018, *108*, 2015–2047. DOI:10.1257/aer.20141745.