Supplemental Appendix

Unconditional Convergence in Manufacturing: A Reassessment

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A.1 Country Lists

Countries in the EETD

East Asia: Cambodia, China, Chinese Taipei, Hong Kong, Indonesia, Japan, Laos, Malaysia, Myanmar, Philippines, Republic of Korea, Singapore, Thailand, Viet Nam;

Europe: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Russia, Spain, Sweden, Turkey, United Kingdom;

Latin America & the Caribbean: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru;

Middle East, North Africa & Central Asia: Egypt, Israel, Morocco, Tunisia;

South Asia: Bangladesh, India, Nepal, Pakistan, Sri Lanka;

Sub-Saharan Africa: Botswana, Cameroon, Ethiopia, Ghana, Kenya, Malawi, Mauritius, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, Zambia;

Western offshoots: Australia, Canada, New Zealand, United States;

Countries added to ETD to construct EETD

Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, New Zealand, Norway, Portugal, Russia, Spain, Sweden, United Kingdom, United States

Table A1 reports the distribution of GDP/worker for 1990 relative to the United States in the ETD[1]

Table A1: Distribution of GDP/Worker Relative to the U.S. (ETD, 1990)

Bins	< 0.05	$[0.05, 0.10)$	$[0.10, 0.20)$	$[0.20, 0.50)$	$[0.50, 0.75)$	$[0.75, 1.00]$	> 1.00
Countries	14	9	9	14	4	1	0

Table A2 reports the distribution of the average annual GDP / worker growth rates during the period 1990–2018 for all 51 countries in the ETD and for the 32 countries with an initial GDP / worker less than 20% of the US level.

[1] GDP at current PPP is from PWT10.01.

Table A2: Distribution of Average Annual Growth Rates of GDP/Worker (ETD, in %)

Bins	< 1.0	$[1.0, 2.0)$	$[2.0, 3.0)$	$[3.0, 4.0)$	$[4, 5)$	> 5
All Countries	11	8	12	15	2	3
Poorest 32 Countries	4	5	6	12	2	3

Overlap of EETD and UNIDO databases 1995–2005, 48 countries

Australia, Austria, Belgium, Bolivia, Brazil, Canada, China, Chinese Taipei, Colombia, Costa Rica, Denmark, Ecuador, Egypt, Ethiopia, Finland, France, Ghana, Greece, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Malawi, Malaysia, Mauritius, Mexico, Morocco, Netherlands, New Zealand, Norway, Peru, Philippines, Portugal, Republic of Korea, Russia, Senegal, Singapore, South Africa, Spain, Sweden, Thailand, Turkey, United Kingdom, United States.

EETD Countries with GDP pc less than 20% of the U.S. in 1990

Burkina Faso, Bangladesh, Bolivia, Brazil, China, Cameroon, Egypt, Ethiopia, Ghana, Indonesia, India, Kenya, Cambodia, Laos, Sri Lanka, Lesotho, Morocco, Myanmar, Mozambique, Malawi, Nigeria, Nepal, Pakistan, Peru, Philippines, Rwanda, Senegal, Thailand, Tanzania, Uganda, Viet Nam, Zambia.

A.2 Benchmarking EETD using alternative databases

To evaluate the reliability of the EETD database, we will benchmark it using alternative databases, which are generally considered to be of high quality. In particular, we will use the Penn World Tables (PWT) which is considered the gold standard of international income comparison, data from ILO, and finally the World Development Indicators to benchmark EETD and UNIDO. We will rely on regression analysis when we make the comparisons.

We start with comparing GDP per worker at current PPP in EETD and in PWT in three years, 1990, 2005, and 2018 which span the whole sample period 1990-2018 by running the following log-linear regression

$$\log LP^{PPP}_{pwt,t} = \phi_0 + \phi_1 \log LP^{PPP}_{eetd,t} \qquad t \in \{1990, 2005, 2018\}.$$

We used the PPP from PWT10.01 to convert the value added in EETD to isolate the difference in productivity measure rather than difference in valuations. The results can be found in Table A3. The F-tests imply that we cannot reject the null hypotheses that slopes are equal to 1, and the intercepts are equal to zero. In addition, the R^2 is close to 1 indicating how close the two

Table A3: Labor Productivity in EETD and in PWT10.01

Cross-sectional regressions, 68 countries

	1990	2005	2018
ϕ_1	0.9980	0.9981	1.0224
$p-$value	{0.0000}	{0.0000}	{0.0000}
ϕ_0	0.0507	0.0861	−0.1715
$p-$value	{0.7011}	{0.3140}	{0.2641}
R^2	0.9868	0.9929	0.9902
Number of countries	68	68	68
$F-$test: $H_0 : \{\phi_1 = 1\}$	0.0219	0.0446	2.3427
$p-$value	{0.8829}	{0.8333}	{0.1306}
$F-$test: $H_0 : \{\phi_0 = 0\}$	0.1486	1.0293	1.2688
$p-$value	{0.7011}	{0.3140}	{0.2641}

datasets are. Thus, statistically the two datasets provide the same aggregate labor productivity measure.

Next we turn to the comparison of manufacturing employment, $MEMP$, from ILO and manufacturing value added, MVA, expressed in USD, from the World Development Indicators (WDI) with the equivalents in EETD. We normalize both variables with population, POP, taken from PWT10.01. We then run the regression

$$\log\left(\frac{MEMP_{ilo}}{POP}\right) = \phi_0 + \phi_1 \log\left(\frac{MEMP_{eetd}}{POP}\right)$$
$$\log\left(\frac{MVA_{wdi}}{POP}\right) = \phi_0 + \phi_1 \log\left(\frac{MEMP_{eetd}}{POP}\right)$$

to compare the alternative databases with EETD (see Table A4). We start with ILO employment data. Although the point estimates of ϕ_1 and ϕ_0 are close to one, and to zero, respectively, the $F-$tests imply ϕ_1 and ϕ_0 are statistically significantly different from one and from zero, respectively. Thus, although the EETD and ILO manufacturing employment data are highly correlated, there are statistically detectable differences between the ILO and EETD data. We turn now to the MVA data in the WDI. The point estimates of ϕ_1 and ϕ_0 are very close to one, and to zero, respectively, the $F-$tests imply ϕ_1 is statistically significantly different from one at the 5% level, but not at 1% level. In addition, ϕ_0 is not significantly different from zero. Given the very high R^2, we can conclude that indeed the two datasets are statistically the same.

Next we construct labor productivity measures using the three possible combinations of manufacturing value added and employment across the three different datasets. In particular,

Table A4: Manufacturing Employment in ILO and Manufacturing Value Added in WDI and the equivalents in EETD variables normalized with population

	ILO employment to population ratio	WDI manufacturing value added per capita
ϕ_1	0.9491	0.9909
$p-$value	{0.0000}	{0.0000}
ϕ_0	−0.0956	0.0380
$p-$value	{0.0514}	{0.1967}
R^2	0.8349	0.9743
Number of observations	898	1,773
Number of countries	63	67
$F-$test: $H_0 : \{\phi_1 = 1\}$	8.3567	5.4194
$p-$value	{0.0039}	{0.0200}
$F-$test: $H_0 : \{\phi_0 = 0\}$	3.8051	1.6681
$p-$value	{0.0514}	{0.1967}

we run the following regressions

$$\log\left(\frac{MVA_{eetd}}{MEMP_{ilo}}\right) = \phi_0 + \phi_1 \log\left(\frac{MVA_{eetd}}{MEMP_{eetd}}\right) \tag{1a}$$

$$\log\left(\frac{MVA_{wdi}}{MEMP_{eetd}}\right) = \phi_0 + \phi_1 \log\left(\frac{MVA_{eetd}}{MEMP_{eetd}}\right) \tag{1b}$$

$$\log\left(\frac{MVA_{wdi}}{MEMP_{ilo}}\right) = \phi_0 + \phi_1 \log\left(\frac{MVA_{eetd}}{MEMP_{eetd}}\right) \tag{1c}$$

where MVA is measured in USD.

Table A5: Three Productivity Measures
Regressor in all cases is labor productivity in EETD

	(1)	(2)	(3)
	$\log\left(\frac{MVA_{eetd}}{MEMP_{ilo}}\right)$	$\log\left(\frac{MVA_{wdi}}{MEMP_{eetd}}\right)$	$\log\left(\frac{MVA_{wdi}}{MEMP_{ilo}}\right)$
β	0.9770	0.9898	0.9343
$p-$value	{0.0000}	{0.0000}	{0.0000}
Constant	0.1843	0.0768	0.6350
$p-$value	{0.0220}	{0.1509}	{0.0000}
R^2	0.9771	0.9592	0.9573
Number of observations	898	1773	880
Number of countries	63	67	62
$F-$test: $H_0 : \{\phi_1 = 1\}$	9.6801	3.8691	44.6147
$p-$value	{0.0019}	{0.0493}	{0.0000}
$F-$test: $H_0 : \{\phi_0 = 0\}$	5.2618	2.0650	35.0912
$p-$value	{0.0220}	{0.1509}	{0.0000}

The results can be found in Table A5. The R^2 is high in all three cases, indicating a strong correlation between labor productivity in EETD and the other three permutations we constructed. However, the $F-$tests imply that the slopes are significantly different from 1, and the intercepts significantly different from zero. In conclusion, there is a strong correlation between the labor productivity levels in manufacturing between EETD and the alternative constructions suggesting strong similarities, but it is not as strong as in the case of when we compared aggregate labor productivity in EETD and PWT.

However, ultimately the question is whether these alternative productivity measures lead to different convergence results from what we obtained in the main body of the paper. The answer is they do not. We run our convergence regressions using the three productivity measures as defined in the left hand side in equation (1). For comparability reasons, we estimate all three regressions on a sample which overlaps with EETD. The results are in Table A6. The three point estimates of the convergence parameters, β, are small and statistically not significant. Thus, the differences between the three productivity measures do not affect the key result, namely, that we do not find unconditional convergence.

Table A6: Convergence Regressions for the Three Productivity Measures
all three estimations is based on a subsample of EETD

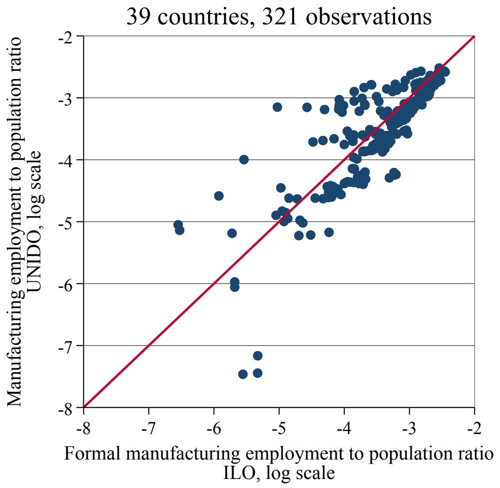
	(1)	(2)	(3)
	$\Delta \log \left(\frac{MVA_{eetd}}{MEMP_{ilo}}\right)$	$\Delta \log \left(\frac{MVA_{wdi}}{MEMP_{eetd}}\right)$	$\Delta \log \left(\frac{MVA_{wdi}}{MEMP_{ilo}}\right)$
β	0.0011	−0.0046	−0.0031
$p-$value	{0.7244}	{0.1047}	{0.4606}
Number of observations	768	1,706	751
Number of countries	50	67	50
Units	USD	USD	USD
Time fixed effects	Yes	Yes	Yes
Country fixed effects	No	No	No

A.2.1 Coverage Ratio and Formal Employment

Figure A1: Coverage Ratio and Formal Employment

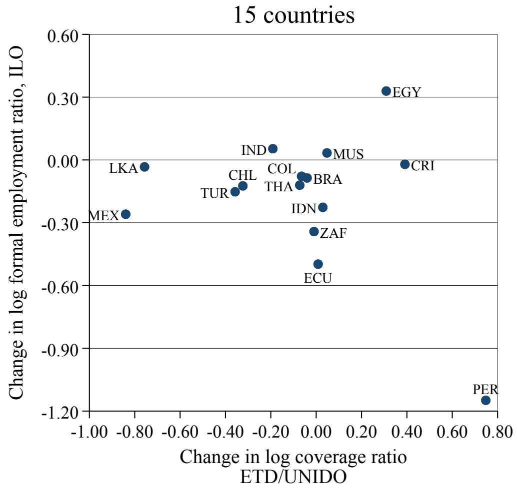
(a)

UNIDO Manufacturing Employment vs.
ILO Formal Manufacturing Employment
population from PWT10.01



(b)

Change in Coverage Ratio vs.
Change ILO Formal Manufacturing Employment



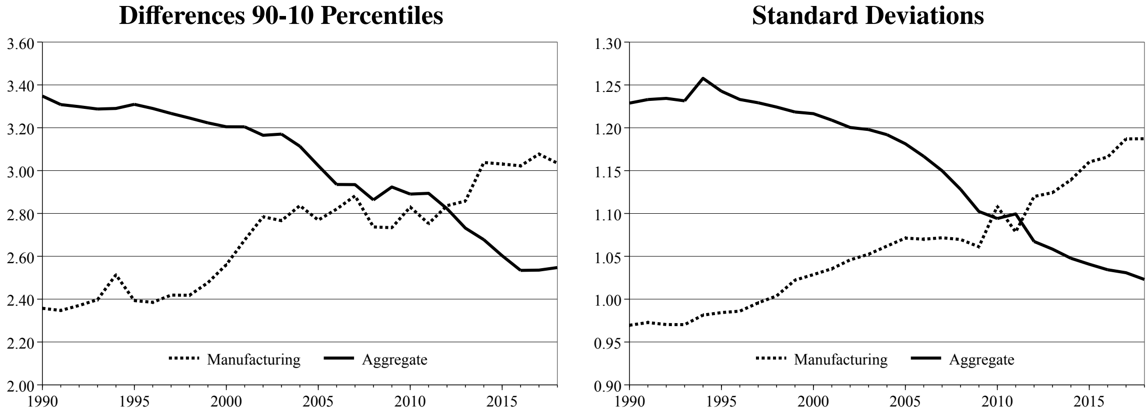
A.3 Robustness and Additional Evidence

A.3.1 Robustness Results

Table A7: Geographic Robustness of Convergence Regressions (EETD, 1990–2018)

	Aggregate	Agriculture	Manufacturing	Market sevices
	Sub-Saharan African countries excluded			
β	−0.0115	−0.0030	−0.0045	−0.0099
$p-$value	{0.0000}	{0.0275}	{0.1897}	{0.0000}
Number of observations	1,484	1,484	1,484	1,484
Number of countries	53	53	53	53
Units	PPP	PPP	PPP	PPP
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No
	South and East Asian countries excluded			
β	−0.0041	−0.0037	0.0075	−0.0012
$p-$value	{0.0019}	{0.0148}	{0.0425}	{0.6058}
Number of observations	1,316	1,316	1,316	1,316
Number of countries	47	47	47	47
Units	PPP	PPP	PPP	PPP
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No
	Latin American & Caribbean countries excluded			
β	−0.0074	−0.0041	−0.0013	−0.0056
$p-$value	{0.0000}	{0.0006}	{0.7263}	{0.0087}
Number of observations	1,652	1,652	1,652	1,652
Number of countries	59	59	59	59
Units	PPP	PPP	PPP	PPP
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No
	Middle Eastern and North African countries excluded			
β	−0.0074	−0.0033	−0.0015	−0.0057
$p-$value	{0.0000}	{0.0061}	{0.6546}	{0.0050}
Number of observations	1,792	1,792	1,792	1,792
Number of countries	64	64	64	64
Units	PPP	PPP	PPP	PPP
Time fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	No	No	No	No

Figure A2: Cross-country Dispersion in Log Productivity
(68 countries in EETD, current PPP)



A.3.2 Measures of σ convergence

The concept of σ-convergence refers to a decrease in cross-sectional dispersion over time. To study σ-convergence, we consider two measures of dispersion: the $90-10$ percentile difference in log productivity and the standard deviation of log productivity. Figure A2 shows time series for both measures for the manufacturing sector and the aggregate economy over the period 1990–2018. Both measures offer the same striking message: whereas there has been a large decrease in the cross-sectional dispersion of aggregate productivity over this time period (roughly 25 percent for both measures), there has been a similarly large increase in the cross-sectional dispersion of manufacturing productivity.

A.3.3 The Role of Different Conversion Factors for Domestic Productivity Measures

To evaluate the impact of different productivity measures on the results for β convergence, we examine two key questions. First, do the benchmark year data from the EETD provide evidence that the law of one price (henceforth LOP) holds, the key assumption of Rodrik's analysis? Second, do the productivity data in USD, derived from EETD, provide evidence for unconditional convergence in manufacturing? The answer to both questions is a clear no.

First, we test whether LOP holds on the data of the three benchmark years in EETD for which PPPs have been constructed. Since for each year the units of PPP have been chosen such that the values of productivity in USD and in PPP are equal for the U.S.:

$$LP_{US}^{USD} = LP_{US}^{PPP},$$

we can run the following regression for the 68 countries in the $EETD$:

$$\log LP_j^{PPP} = \phi_0 + \phi_1 \log LP_j^{USD} + \varepsilon_j, \tag{2}$$

where ε_j is an error term. Rodrik's use of productivity measured in USD to directly proxy for productivity measured in PPPs amounts to imposing $\phi_0 = 0$ and $\phi_1 = 1$.

Figure A3: Manufacturing Productivities in PPP vs USD

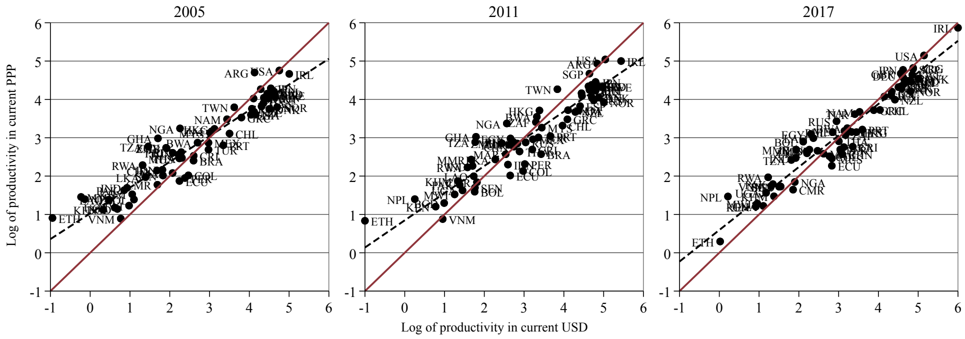


Figure A3 displays the regression results of (2) for the three benchmark years. The graph clearly shows that the conditions $\phi_0 = 0$ and $\phi_1 = 1$ are violated by the data. Table A8 provides the statistical evidence for the same effect. Both ϕ_0 and ϕ_1 are statistically significantly different from zero. More importantly, the $F-$tests for $H_0 : \{\phi_1 = 1\}$ and $H_0 : \{\phi_0 = 0\}$ mean that we reject the null hypothesis $H_0 : \phi_1 = 1$ and $H_0 : \{\phi_0 = 0\}$, that is, we reject that LOP holds.

Table A8: Manufacturing Productivities Regression
(68 countries in EETD)

	2005	2011	2017
ϕ_1	0.6719	0.7069	0.8215
$p-$value	{0.0000}	{0.0000}	{0.0000}
ϕ_0	1.0286	0.8518	0.5958
$p-$value	{0.0000}	{0.0000}	{0.0000}
R^2	0.8912	0.8727	0.9365
$F-$test: $H_0 : \{\phi_1 = 1\}$	122.4551	63.4865	46.5647
$p-$value	{0.0000}	{0.0000}	{0.0000}
$F-$test: $H_0 : \{\phi_0 = 0\}$	101.0017	39.4749	34.4747
$p-$value	{0.0000}	{0.0000}	{0.0000}

To assess the role of differences in data construction, we run the convergence regression (3) using both our productivity measure in current PPP and for Rodrik's productivity measure in

Table A9: Convergence Regressions for Manufacturing – PPP vs. USD (68 countries in EETD)

Panel I.	**1990–2018**	
	(1)	(2)
β	−0.0015	−0.0053
$p-$value	{0.6638}	{0.0420}
Observations	1,904	1,904
Units	PPP	USD
Time fixed effects	Yes	Yes
Country fixed effects	No	No
Panel II.	**1995–2005**	
β	0.0017	0.0033
$p-$value	{0.6716}	{0.3665}
Observations	748	748
Units	PPP	USD
Time fixed effects	Yes	Yes
Country fixed effects	No	No

current USD prices. As before, we run the regressions both with and without country fixed effects. Differently than before, we run the regressions both for our entire sample period 1990–2018 and for the subperiod 1995–2005. The decade 1995–2005 is informative because Rodrik (2013) paid particular attention to it, reflecting that the UNIDO data stop in 2005 and have the most balanced sample during 1995–2005.

Table A9 presents the results. The main message of the table is that the differences in methods for calculating comparable productivity measures are not crucial for the unconditional β-convergence results. In particular, while the point estimates using Rodrik's data construction are somewhat larger than using our data construction for the entire 1990–2018 period, they are still small compared to his point estimates. Moreover, when focusing on the 1995–2005 subperiod, both β estimates for unconditional convergence are effectively zero. When considering conditional convergence, each data-construction method implies significant convergence for both the overall time period and the 1995–2005 subperiod, though the estimates of conditional convergence are somewhat larger using the Rodrik construction.

We conclude that the starkly different results that we obtain for unconditional convergence compared to Rodrik are not due to the different methods for constructing comparable productivity levels.