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# TFP in the Manufacturing Sector: Long-Term Dynamics, Country and Regional Comparative Analysis

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**Abstract:** We employ a recent empirical strategy to estimate country-specific and time-varying total factor productivity (TFP) levels for the manufacturing sector of 63 countries over 40 years. The methodology is based on estimated country-specific production functions while accounting for cross-section dependence and nonstationary series. We then analyze the derived TFP series across the entire sample and several regional groupings (Asia, Europe and Central Asia (ECA), Middle East and North Africa (MENA), Latin America and the Caribbean (LAC), and the USA). Our analysis reveals the following. Firstly, the TFP that is common across countries has an upward trend with a significant slump in 2008. Secondly, the leading positions in terms of productivity in the manufacturing sector remained the prerogative of major developed countries. Thirdly, several countries succeeded in climbing the ladder through outstanding productivity growth. Fourthly, despite a clear hierarchy in terms of manufacturing productivity across regional blocs, all regions witnessed an increase in productivity over the period. Fifthly, there is evidence of convergence in the TFP across countries and within Asia and ECA before a potential break in 2008.

**Keywords:** manufacturing sector; TFP; productivity; augmented mean group estimator; common factor; stochastic convergence



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## 1. Introduction

Productivity is the main driver of economic growth (Hall and Jones 1999; Easterly and Levine 2001; Caselli 2005; Gordon 2015; Makieła et al. 2022), and differences in growth-paths exist among countries and sectors. These differences reflect the efficiency of the production process in the allocation and the use of inputs (Easterly and Levine 2001). In this sense, productivity for classical economists such as Adam Smith and David Ricardo can increase because of labor division, specialization, and trade. For Hicks (1939) and Schumpeter (1942), entrepreneurship and creative destruction lead to innovations that would increase productivity. For Lewis (1954), Kuznets (1957), and Chenery (1960), structural transformation that reallocates resources to the most productive sectors is the source of economic growth.

With the work of Solow (1956) and Swan (1956), productivity became the core of the neoclassical growth theory. The two authors developed a growth model for competitive economies with a constant return to scale production function. Output growth rate in their deterministic model is determined by changes in physical capital, labor, and total factor productivity (TFP). TFP is hence the portion of output growth that is not attributed to capital and labor accumulation. It is assumed to be exogenous and is described as a residual measure of productivity growth due to technical change and know-how. The growth accounting approach, derived from deterministic models, measures TFP as a residual component of GDP growth. Abramovitz (1956) interprets it as a "measure of our ignorance" that captures, among other things, organizational innovation and the political and institutional environment in the country. Parallel to the theoretical explanation of

TFP, empirical research explored it at country (Serranito 2017; Malik and Masood 2021), industry (Biatour et al. 2011; Chaffai et al. 2009; Gehringer et al. 2013; Choudhury and Das 2018; Haider et al. 2021), as well as firm levels (Daoud and Sekkat 2017; Elshennawy and Bouaddi 2018; Tekleselassie et al. 2018; Børing 2019; Añón Higón et al. 2022).

Based on country-specific production functions estimated over 1980–2020, we derive the TFP in the manufacturing sector of 63 countries. We also analyze manufacturing TFP dynamics over the sample and across different regional blocs[1]. The motivation of our empirical investigation is twofold. First, the manufacturing sector is paramount for economic development. Moreover, industrialization continues to play a pivotal role in the economic expansion of many developing countries (Haraguchi et al. 2017). Indeed, compared to agriculture and services, the industrial sector has more pronounced backward and forward linkages across the economy. Thus, an expansion of the manufacturing sector reverberates across the whole economy via multiplier effects (Haraguchi et al. 2017). In addition, the sector's capacity of realizing high levels of capital accumulation as well as economies of scale, makes it particularly conducive for productivity growth (Haraguchi et al. 2017). Second, a notable part of the differences in per capita income across countries, after controlling for physical and human capital, is attributed to disparities in TFP (Kijek and Matras Bolibok 2020).

Against this backdrop, our empirical investigation aims to accomplish the following: (i) examine the manufacturing TFP evolution over the covered period; (ii) identify leading/lagging countries, as well as countries that knew a substantial improvement in their manufacturing TFP over the studied period; and (iii) investigate a potential convergence process in manufacturing productivity across countries over the covered period.

To achieve our objectives, we model country-specific TFP as unobservable inputs in a Cobb-Douglas production function. We allow part of the TFP to be common to all countries (e.g., global dissemination of knowledge) and the other part to be country-specific. To do so, we employ the augmented mean-group (AMG) estimator and build on the empirical strategy of Eberhardt and Teal (2020). Their methodology casts the production function in a common factor setting that accommodates three issues that have rarely been dealt with in previous studies. First, it allows for heterogeneous production functions. It therefore acknowledges the possibility that countries of different development levels and dissimilar country-specific factors are likely to have different production processes. Such differences are explained by the imperfections in the market for knowledge because of monopolistic licensing fees, the requirements for local technology absorption, and protectionist policies (Pack 1994). This is in line with the diversity of growth experiences among countries (Mankiw et al. 1992; Pack 1994; Durlauf 2001; Durlauf et al. 2005). Second, it accounts for cross-sectional dependence across countries, notably in the TFP series. In fact, countries may be subject to common technology shocks (Martin and Mitra 2002), and affected by global disturbances and/or localized ones. If not tackled properly, this cross-country correlation may bias the results (O'Connell 1998). Third, it appreciates that the TFP, like the other variables of the production function, may exhibit high levels of persistence in the long-run. It accommodates the possibility that, for some countries, those variables may not be stationary, avoiding the problem of spurious regression (Nelson and Plosser 1982).

Our results show the following. Firstly, the common TFP advancement over the covered period is essentially upward-oriented with the main exception of the 2008 crisis. Secondly, the leaders in manufacturing TFP are the top developed countries like the USA, Japan, the UK, Germany, and France. Thirdly, many countries progressed over the period; this is the case for Vietnam, Ireland, Turkey, India, and Egypt to cite a few. Fourthly, all regional groupings knew an increase in their (mean) TFP level across the time horizon. Finally, a convergence process seems to have been at play, both across the sample countries and within some regional groupings. However, it has been brought to a halt by the 2008 crisis.

In addition to the methodological novelty on which our empirical strategy relies, our investigation is, to the best of our knowledge, the first to set up a cartography of manufacturing TFP that covers a large number of countries over four decades. In particular, researchers whose work revolves around manufacturing TFP can use our derived TFP series (available in the online resource excel file) in their future research. Moreover, our analysis bears many insights that can be of high interest to policy-makers. Particularly, those responsible for designing measures and policies impacting the manufacturing sector.

The paper is structured as follows. In Section 2, we overview the theoretical and empirical approaches used in the derivation of the TFP. In Section 3, we discuss the selected sample and the economic contribution of the manufacturing sector in the selected countries. In Section 4, we discuss the methodology and the data used. In Section 5, we expose our findings related to the TFP rankings, time-evolution, and convergence. Section 6 concludes.

## 2. Literature on TFP Estimation

Total factor productivity is calculated as the ratio of total output over a weighted average of inputs (Amato et al. 2022). It measures the relationship between output and inputs used in the production process. TFP is an empirical concept rather than a deeply founded theoretical concept. In fact, there is no clear theory of TFP (Prescott 1998). Three different interpretations were proposed in the literature (Carlaw and Lipsey 2003; Lipsey and Carlaw 2004). The first one interprets TFP as technological knowledge. Hence, changes in TFP measure technological change. The latter is estimated as a residual from a log-linearized production function. It is considered the fraction of output growth that is not explained by the accumulation of inputs. The second one views TFP as the gains in output that are above the costs necessary for the creation of technological changes (these costs are called development costs). Hence, TFP growth measures returns above development costs. If these excess returns are null, then investing in new technologies will have the same rate of return as investing in existing technologies. Hence, changes in TFP occur because of differences in the marginal productivities for investing in new and existing technologies. The third one interprets TFP as a measure of our ignorance. TFP in this case would measure anything.

The objective in this section is to give a practical overview of the different estimation techniques used in the empirical literature in order to derive TFP. Carlaw and Lipsey (2003) and Del Gatto et al. (2011) classify these techniques under two separate methodologies: (i) deterministic methodologies (data envelopment analysis, free disposal Hull model, growth accounting approach, and efficiency indices) and (ii) econometric methodologies (growth regressions and stochastic frontier analysis). Given the methodology we adopt in this paper in order to derive TFP in the manufacturing sector, this literature review focuses on the growth regressions approach. The latter is a model-based approach that identifies a structural equation to estimate TFP from aggregate data. It stems from the seminal work of Mankiw et al. (1992) (hereafter MRW). Unlike the growth accounting approach based on Solow (1956, 1957), TFP is not estimated as a residual but instead is purged from noise.

The canonical growth regressions, with capital ($K$) and labor ($L$), usually estimated in the literature in order to model TFP, are of two forms. The first one is a log-linearized Harrod-neutral technology production function, $Y = K^{\alpha}(AL)^{\beta}$, where technology ($A$) is labor augmenting and $AL$ is defined as "effective labor" (MRW; Islam 1995; Pavcnik 2002; Levinsohn and Petrin 2003; Di Liberto et al. 2008). Advances in technology increase in this case the productivity of labor. The second one is a log-linearized Hicksian-neutral production function, $Y = AK^{\alpha}L^{\beta}$. Technology in this case raises the marginal productivity of capital and labor in the same proportion (Ladu 2010; Marrocu and Paci 2011, 2012a, 2012b; Berlemann and Wesselhöft 2012; Dettori et al. 2012; Marrocu et al. 2013; Ladu and Meleddu 2014; Mitze 2014; Capello and Lenzi 2015; Biagi and Ladu 2018; Schatzer et al. 2019; Siller et al. 2021). Hence, advances in technology will shift the production possibility frontier outward, increasing the production set. Coefficients $\alpha$ and $\beta$ in the two production functions above are the factor elasticities.

The seminal work of MRW extends the Solow-Swan model and estimates a Harrod-neutral production function assuming constant returns to scale. They consider the pooled panel approach and exploit the panel structure of a sample of countries. They assume homogeneous elasticities across countries. In their model, the level of technology at an initial point of time is decomposed into a constant and a country-specific unobservable factor considered a purely random phenomenon (the error term). Consequently, the constant measures the mean efficiency level across countries and over time. The error term is the country-specific deviation from that mean. MRW consider the error term uncorrelated with the explanatory variables. Under this assumption of error independency, the growth regression is estimated using ordinary least squares (OLS). Berlemann and Wesselhöft (2012) consider a Hicksian-neutral production function and estimate regional TFP for German municipalities using a cross-sectional approach. Similar to MRW, they calculate the region's level of technology as a constant and a region-specific unobservable factor, and estimate their model using OLS. These two approaches obtain TFP as the residual of output that cannot be explained by inputs. As such, TFP does not only comprise the effects of technological innovation but also picks up other unwanted factors such as measurement errors and missing variables. However, OLS estimation of production functions is subject to simultaneity or endogeneity problem because productivity and inputs are likely to be correlated. This would lead to biased production estimates (Van Beveren 2012).

Islam (1995) develops MRW's model for a panel data framework and assumes that technology varies non-randomly across countries. He considers that the initial level of technology is determined by a country-specific fixed effect plus a country-time dependent error term. He relaxes the independency assumption supposed by MRW and assumes the random shock to be correlated with the explanatory variables. Islam (1995) estimates the growth equation using the least squares with dummy variables (hereafter LSDV) estimator and the minimum distance (MD) estimator. Others like Pavcnik (2002) and Levinsohn and Petrin (2003) use fixed effects (FE) estimator. Though the FE overcomes the simultaneity bias, it does not perform well. In practice, it often leads to low estimates of the elasticity of capital (Van Beveren 2012). Moreover, when the time dimension is small, LSDV and FE estimators produce downward biased estimates.

Based on Islam (1995) work, Di Liberto et al. (2008) estimate, in a dynamic panel data framework, a growth equation using the Arellano and Bond (1991) estimator (hereafter GMM-AB). They relax the time-invariant nature of productivity imposed in the FE model. GMM-AB allows productivity to be decomposed into a fixed effect and an autoregressive AR(1)-component. It has the advantage of producing consistent estimates in small samples when some explanatory variables are endogenous and the instruments are correctly chosen. Van Beveren (2012) makes use of Blundell and Bond (2000) estimator (hereafter GMM-BB), arguing that GMM-AB produces downward biased estimates in the presence of nonstationary input variables while GMM-BB does not. Van Beveren (2012) notes that the instrumental variable estimation assumes that productivity evolves exogenously over time. This assumption is likely to be invalidated if not all the inputs are controlled for in the production function.

Other researchers relax the assumption of constant returns to scale and derive TFP from a Hicksian-neutral production function. They exploit the panel structure of the data and consider the level of technology to be time dependent. These studies model country and time-specific TFP levels in three different ways. First, as a constant plus time effects and a country-time dependent error term (Marrocu et al. 2013). Second, as a constant plus country and time effects and a country time-dependent error term (Miller and Upadhyay 2002; Bournakis and Mallick 2018). Third, as country and time effects plus a country time dependent-error term (Marrocu and Paci 2011, 2012a, 2012b). This FE approach derives TFP levels directly from the country and time effects excluding the error term. This approach considers TFP a model parameter of the production function and assumes TFP growth rate to be equal across countries. The country effects capture the efficiency in technology production, and the time effects capture knowledge accumulation or common shocks that affect all countries simultaneously. To avoid a potential endogeneity problem, TFP can be obtained using a two-stage least squares (2SLS) estimation method (Dettori et al. 2012;

Marrocu and Paci 2012a, 2012b; Marrocu et al. 2013; Biagi and Ladu 2018). One can also control for spillovers and endogeneity by using a spatial 2SLS estimation method (Marrocu and Paci 2011; Dettori et al. 2012). Ladu (2010) estimates the growth equation using the group mean fully modified OLS (FMOLS) estimator and the generalized least squares (GLS) estimator. However, this estimation approach fails to account for country-specific shocks such as changes in the country's monetary policy, or fiscal policy or political uncertainties.

Schatzer et al. (2019) and Siller et al. (2021) augment the FE approach discussed above by adding a unit-specific time trend when calculating TFP. They obtain TFP levels from estimated country fixed effects, time effects, as well as unit-specific time trend. This approach derives TFP from the individual model parameters of the production function. The fixed effects reflect the initial TFP level, whereas the remaining two components capture TFP evolution: time effects reflect universal TFP evolution as well as common shocks and the specific time trend represents the long-term unit-specific TFP growth rate. Contrary to the FE approach, TFP growth rate is country-specific. To tackle the problem of endogeneity and spillover effect, the authors use a 2SLS estimator with spatial error. Schatzer et al. (2019) have shown that modeling TFP of a cross-sectional unit (region/country) at a given point in time as determined by an initial level, universal shocks, and a unit-specific TFP growth rate has several advantages compared to alternative models. In particular, it yields unbiased results with no misspecification. However, this approach does not account for the possible nonstationarity of the variables. This is not the be ignored when working with panel data with long-time series.

Recently, Eberhardt and Teal (2020) extended the above framework and proposed a new approach that considers the TFP level of a given country at any point in time to have two components—an initial TFP value and a TFP evolution. However, they suggest a new estimation approach that tackles three recurrent econometric problems: potential endogeneity of the regressors, presence of cross-sectional dependence in the variables, and non-stationarity of the variables. Moreover, they derive TFP from country-specific production functions, allowing heterogeneity in the coefficients. In view of the flexibility of the Eberhardt and Teal (2020) approach, we adopt it to derive the manufacturing TFP series, and explain it thoroughly in Section 4.

## 3. The Economic Contribution of the Manufacturing Sector in Our Sampled Countries

Using country-specific production functions, we derive the TFP series of the manufacturing sector for 63 countries. The selected countries are listed in Appendix A and the period of analysis is 1980–2020. On the one hand, 1980 is a year where a large number of countries has significant observations for the value added, employment, and the gross fixed capital formation (GFCF). On the other hand, 2020 is the last year with available data. Other countries were excluded from the analysis because they do not have the minimum number of observations required to estimate country-specific production functions. Details of the data collection and the definition of the variables can be found in Appendix B.

We highlight here below the economic contribution of the manufacturing sector in the selected countries. Our selected countries can be grouped according to the World Bank classification into four main geographical regions: (i) Europe and Central Asia (ECA), (ii) Middle East and North Africa (MENA), (iii) East Asia, Pacific and South Asia (Asia), and (iv) Latin America and the Caribbean (LAC).[2] We consider the USA a benchmark country and take it as a standalone region.

Table 1 shows that the USA and the MENA countries have the lowest share of the manufacturing value added in GDP. Both shares are below the sample average and lag behind ECA, Asia, and LAC. While in the case of the USA this is explained by the important contribution of other sectors to GDP (namely services), the MENA figures reflect the preponderance of oil and gas in the economies of the region and their feeble diversification[3]. The top five countries with the highest average share over the period are, by order, Belarus, South Korea, Malaysia, Ireland, and Indonesia. Moreover, six countries from Asia region

(South Korea, Malaysia, Singapore, Indonesia, Philippines, and Japan) are among the top ten.

**Table 1.** Economic contribution of the manufacturing sector across regions.

| | Manufacturing, Value Added (% of GDP) (1980–2020) | Manufacturing, Value Added (Annual % Growth) (1980–2020) | % of Employment in Manufacturing (1991–2020) | Manufactures Exports (% of Merchandise Exports) (1980–2020) |
|---|---|---|---|---|
| ECA | 15.24% | 2.86% | 12.95% | 67.27% |
| Asia | 14.85% | 3.44% | 8.53% | 55.84% |
| LAC | 17.76% | 2.18% | 4.68% | 34.10% |
| MENA | 13.31% | 4.43% | 7.17% | 47.28% |
| The USA | 12.74% | 2.06% | 9.40% | 70.75% |
| Total Sample | 15.19% | 3.23% | 10.69% | 60.17% |

Note: The share of employment in the manufacturing sector is calculated as the number of employed in the manufacturing sector divided by total employment. The latter is available for the period starting in 1991. Source: World Development Indicators (WDI) database published by the World Bank.

When looking at the average annual growth rate of manufacturing value added, we note the noticeable performance of the MENA region. It comes first with an average growth rate of 4.43%, followed by Asia (3.44%), ECA (2.86%), and LAC (2.18%). Remarkably, the 2008 financial crisis and the COVID-19 pandemic that spread out in early 2020 seem to have caused a slump in the growth rate series of the manufacturing value added. In fact, 48 and 49 countries had a negative growth rate, respectively, in 2009 and 2020. The average annual growth rate was −7.45% in 2009 and −3.83% in 2020. Moreover, 92% of the high-income countries in our sample had a negative growth rate in 2009 versus 61% of the middle-income countries[4]. While in the aftermath of the COVID-19 pandemic, 86% of high-income countries and 74% of middle-income countries had negative growth rates. This suggests that the impact of the 2008 financial crisis on the manufacturing sector was mostly at play in high-income countries. On the other hand, the repercussions of the COVID-19 pandemic were more widespread and affected high-income and middle-income countries in comparable proportions.

Furthermore, Table 1 shows the average employment in the manufacturing sector as a percent of total employment between 1991 and 2020. Data before 1991 are not available. We notice that this share was the highest in ECA region (12.95%), followed by Asia (8.53%), MENA (7.17%), and LAC (4.68%) regions. The top ten countries with the highest shares are mostly Eastern European countries (Czechia, Slovenia, Estonia, Germany, Belarus, Hungary, Slovakia, Luxembourg, Singapore, and Romania). Most of the latter countries are high-income countries. Interestingly, these countries had a moderate share of the manufacturing value added in GDP.

Finally, Table 1 sheds light on the share of manufactured exports in total merchandise exports across the regions. The USA and ECA were the top performers with 70.75% and 67.27%, respectively. The two leading regions were followed by the MENA region (47.28%) and the LAC countries (34.10%).

## 4. Empirical Strategy and Data

Our empirical design is twofold. In a first stage, we estimate Cobb-Douglas production functions using data on the manufacturing sector over 1980–2020 and covering 63 countries. At this stage, we generate and analyze TFP estimates in the manufacturing sector. Since the estimation methodology is based on a first-differencing process, the generated TFP series cover the 1980–2019 period. As mentioned previously, the estimation procedure possesses several desirable features yielding unbiased and non-spurious findings. For one, it is couched in a common factor framework and thus accounts for cross-section dependence among variables. Moreover, it is based on country-specific regressions and therefore allows for country-specific production function parameters. Lastly, it accommodates the potential nonstationarity of the variables.

In a second stage, we investigate whether there is evidence of convergence among the sample countries, and within different regional groupings. This is done via a battery of panel unit root (PUR) tests. The remainder of this section explains the steps of our empirical plan and sheds light on the data used.

*4.1. Estimating Production Functions via the AMG Estimator and Deriving TFP Measures*

Various methods can be used to generate TFP measurements. Approaches based on econometric analysis are particularly popular among researchers (Del Gatto et al. 2011; Schatzer et al. 2019). Typically, the starting point is the estimation of a Cobb-Douglas production function with two inputs. TFP estimates are later recovered from the estimated function and can vary in their functional form, depending on the assumed underlying data generating process of the production function (Del Gatto et al. 2011; Schatzer et al. 2019).

The methodology we adopt to generate our manufacturing TFP series is based on the recent approach of Eberhardt and Teal (2020)[5]. To estimate the production function (Equation (A1) of Appendix C) while properly taking account of TFP evolution, Eberhardt and Teal (2020) use the AMG estimator. The latter is an extension to the mean group (MG) estimators (Pesaran and Smith 1995). The innovation of the AMG estimator consists in augmenting the country-based regressions with placeholders that account for the unobserved factors driving the TFP. This augmentation renders AMG estimates robust to cross-section dependence and nonstationary data, while accommodating the possible endogeneity of the regressors (Eberhardt and Bond 2009). Those attributes make the AMG estimator particularly suitable for estimating production functions (Eberhardt and Teal 2013, 2020).

For $i = 1, \ldots, N$ cross-sectional units and $t = 1, \ldots, T$ years, the below summarizes the AMG-estimation strategy:

$$Stage\ 1: \ \Delta y_{it} = \beta^l \Delta l_{it} + \beta^k \Delta k_{it} + \sum_{t=2}^{T} r_t \Delta D_t + u_{it} \ \Rightarrow \ \hat{r}_t = C\hat{D}P_t \tag{1}$$

$$Stage\ 2: \ y_{it} = \alpha_i + \beta_i^l l_{it} + \beta_i^k k_{it} + g_i t + d_i C\hat{D}P_t + u_{it} \ \Rightarrow \hat{\beta}^c_{AMG} = N^{-1} \sum_{i=1}^{N} \beta_i^c ; c = l,k \tag{2}$$

The first stage is a pooled ordinary least squares estimation of the production function, with the following variables (in *ln* and expressed in first differences): value added ($y_{it}$), labor ($l_{it}$), capital ($k_{it}$); a set of year dummies ($D_t$) (also expressed in first differences); and a white noise ($u_{it}$). Estimates of year dummies represent a "common dynamic process" (CDP). It is the time evolution of unobservable factors along sample countries. Economically, the CDP is interpreted as the progress of common TFP. Stage 2 represents $N$ panel-specific regressions whereupon parameter estimates are averaged across countries[6]. The country-based production functions are extended to include country-specific linear trends ($t$) as well as the estimated CDP from stage 1.

Eberhardt and Teal (2020) demonstrate that when parameters are country specific, country-fixed effects can no longer be considered as base year TFP levels. Instead, they devise an approach to derive country-specific TFP levels that is robust to parameter heterogeneity. We adapt their methodology to the case of a production function with two inputs, and present it in four steps.

First, *adjusted* value added is calculated as follows:

$$y_{it}^{adjusted} = y_{it} - \hat{g}_i t - \hat{d}_i C\hat{D}P_t \tag{3}$$

where $y_{it}$ is value added. Estimated parameters ($\hat{g}_i$, $\hat{d}_i$) are extracted from country-specific AMG-estimation of Equation (2). For any given year, $t$ refers to its count value. $C\hat{D}P_t$

corresponds to the value of the common dynamic process at year $t$. $y_{it}^{adjusted}$ is thus value added stripped out of the effect of unobservables over time, including TFP progress.

Second, $y_{it}^{adjusted}$ is regressed on inputs to obtain country-specific coefficients $(\hat{a}_i, \hat{b}_i, \hat{c}_i)$:

$$y_{it}^{adjusted} = a_i + b_i l_{it} + c_i k_{it} + \epsilon_{it} \tag{4}$$

Third, base year TFP level is computed as follows:

$$TFP_{i,base\ year} = \hat{a}_i + \hat{b}_i l_{i,base\ year} + \hat{c}_i k_{i,base\ year} \tag{5}$$

where $l_{i,base\ year}$ and $k_{i,base\ year}$ are, respectively, labor and capital stock values of country $i$ in the base year. Thus, country-specific base year TFP is obtained while accounting for parameter heterogeneity and base year values of inputs.

Fourth, TFP is calculated at any particular year $t$ (excluding the base year):

$$TFP_{i,t} = TFP_{i,base\ year} + \hat{g}_i t + \hat{d}_i C\hat{D}P_t \tag{6}$$

Equation (6) posits that country-specific TFP at year $t$ is the sum of base year TFP and TFP evolution over time.

### *4.2. Stochastic Convergence Tests*

PUR tests are used in the literature to examine whether there is evidence of stochastic convergence in macroeconomic series (Fleissig and Strauss 2001; Costantini and Lupi 2005; Carrion-I-Silvestre and German-Soto 2007; Byrne et al. 2009; Escobari 2011; Chapsa et al. 2018). If the difference between a given country's series and the series' reference point is stationary, then an equilibrium relationship exists. This hints at a process of convergence between the two series. A common practice is to consider the top performer among the sample of countries or the average across all countries as the series' reference point.

Among the myriad of PUR tests that are available, we employ three: (i) the Im, Pesaran and Shin (IPS) (Im et al. 2003) test, and two "Fisher-type" tests; (ii) the Maddala and Wu (MW) (Maddala and Wu 1999) test; and (iii) the Phillips and Perron (PP) (Phillips and Perron 1988) test[7]. The tests are based on country-specific Dickey Fuller (DF) regressions, allowing for heterogeneous autoregressive parameters. This property enables different rates of convergence across countries compared to PUR tests that impose the restrictive assumption of a common convergence rate among countries. The null and alternative hypotheses are the same for the three tests: All panels contain unit roots (the null); some panels are stationary (the alternative). The rejection of the null is interpreted as evidence of a convergence process among some countries.

We apply the tests on the following series: $\widetilde{TFP}_{it} = \left(TFP_{it} - \overline{TFP}_t\right)$ where $TFP_{it}$ is country $i$'s manufacturing TFP level in year $t$, and $\overline{TFP}_t$ is the cross-sectional weighted average of manufacturing TFP in year $t$: $\frac{\sum_{i=1}^{N} n_i \times TFP_i}{\sum_{i=1}^{N} n_i}$ with the numbers of observations of each country $(n_i)$ among the set of $N$ countries serving as weights[8]. The basic expression of the country-specific DF regressions on which the tests are implemented is the following[9]:

$$\Delta\widetilde{TFP}_{it} = \alpha_i + \phi_i \widetilde{TFP}_{it-1} + \epsilon_{it} \tag{7}$$

With $\alpha_i$ the country-specific mean, $\phi_i$ the country-specific autoregressive parameter and $\epsilon_{it}$ the error term. The IPS and MW tests are applied on Equation (7) augmented with lags of the dependent variable to purge possible autocorrelation across the errors. The PP test is applied on Equation (7) with an estimator that is robust to autocorrelation among the errors.

*4.3. Data, Sources and Pre-Estimation Analysis*

We use the United Nations Industrial Development Organization's (UNIDO) INDSTAT 2 industrial statistics database to collect data on value added, employment, and GFCF[10]. Monetary variables (value added and GFCF) were originally denominated in US dollars and in nominal terms. We transformed them into real terms by deflating the nominal values by the GDP implicit deflator (in US dollars, base year 2015). We extracted the deflator series from the National Account Main Aggregates Database of the United Nations Statistics Division. To construct the capital stock, we reverted to the perpetual inventory method (see Appendix B).

Our pre-estimation investigation shown in Tables A1 and A2 in Appendix D suggests that our variables exhibit cross-section dependence and are nonstationary processes.

## 5. Findings

*5.1. AMG Estimation Results*

Results of Equation (2) are in Appendix D Table A3. They show that observable inputs (*k* and *l*) affect positively the value added in the manufacturing sector. The CDP, encompassing common TFP evolution, has the largest impact on manufacturing value added. Residuals diagnostics reveal the absence of strong cross-sectional dependence, and indicate the presence of stationary residuals. This suggests that the AMG estimator successfully tackled cross-sectional dependence, hinting at unbiased estimates. Additionally, stationary residuals ensure that our findings do not reflect spurious results.

Figure 1 shows an estimate of the common TFP evolution in the manufacturing sector (from Equation (1)). We find that the covered period comprises four main productivity slowdowns. The first one is in the aftermath of the second oil price shock. The second one coincides with the breakdown of communism. The third one overlaps with the collapse in the information and technology sector that led to the 2001 recession. Finally, the fourth one corresponds to the 2008 financial crisis. The latter seems to have caused the sharpest fall in TFP. The impact of these global shocks that affected the global manufacturing environment is transitory, and the overall pattern of common TFP evolution is upward. The evolution of the TFP for each country is in Appendix D Figure A1.

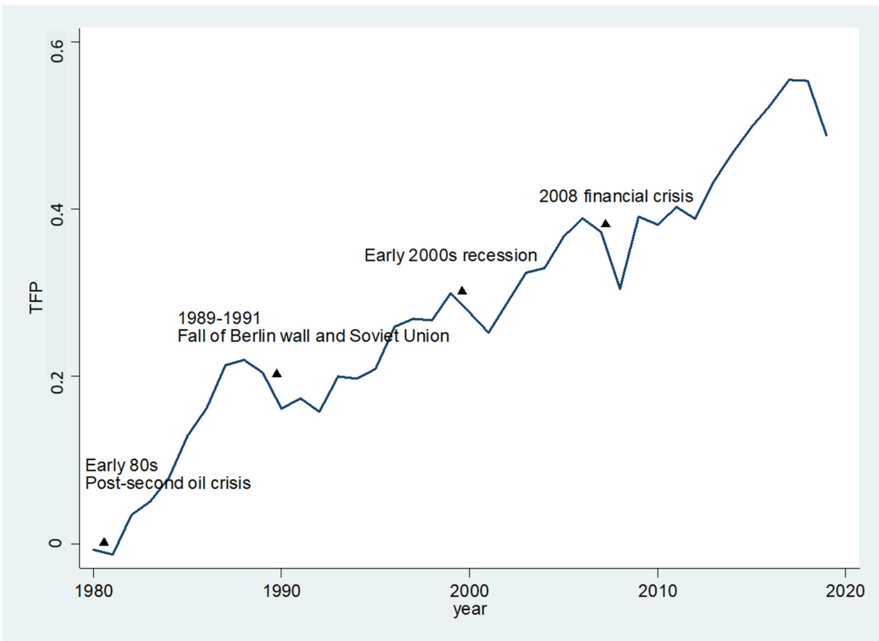


**Figure 1.** CDP evolution (1980–2019). Note: In 2019 the sample of countries drops substantially (from 63 countries to 41 countries).

*5.2. Manufacturing TFP: Global and Regional Comparison*

In Figure 2 we compare the country's TFP in the base year to that in the final year. Dots above the 45-degree line show that the majority of the countries witnessed an increase in their TFP. Countries below the 45-degree line (Australia, Croatia, Luxembourg, Macao, Mongolia, Poland, Spain, Tunisia, Uruguay, and the UK) have a TFP in the final year lower than the TFP in the base year. In Figure 2 we also compare the country's TFP in the base and final years to the sample averages (in the base and final years). All countries in the first quadrant (blue dots, 33 countries) have TFP levels in the base and final years above the sample averages. For those countries, the average share of manufactured exports in total merchandise exports is 67.3%. Moreover, the majority of them are high-income countries (26 countries). Countries in the second quadrant (red dots), namely Belarus, Slovakia, and Viet Nam have a TFP in the base year below the sample average but a TFP in the final year above the sample average. Countries in the third quadrant (green dots, 26 countries) have TFP levels in the base and final years below the sample averages. Those countries have a weak manufacturing sector reflected by a low average share of manufactured exports in total merchandise exports (16.3%). Most of these countries are middle-income countries. Finally, only Croatia falls in the fourth quadrant. Croatia had a TFP level in the base year above the sample average. Though it increased in the final year, its TFP level stayed below the sample mean.

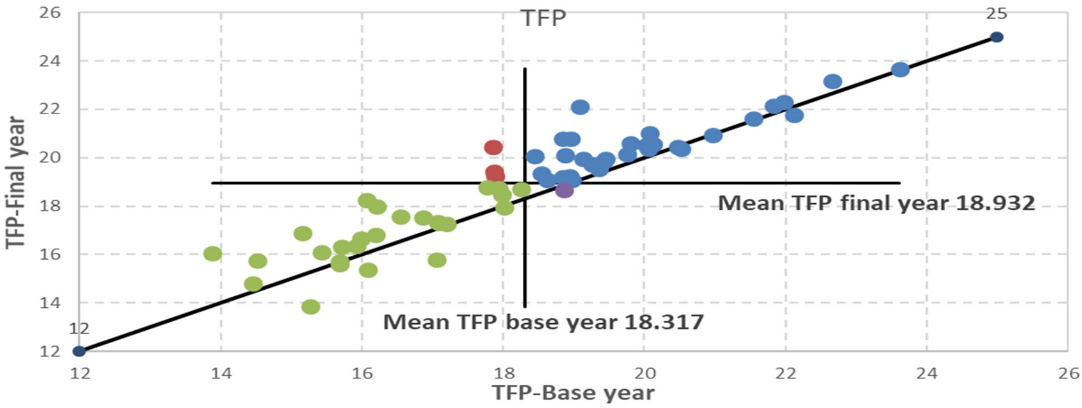


**Figure 2.** Country TFP in the base and final years. Note: (i) Blue dots represent AUS, AUT, BEL CZE, DNK, EGY, FIN, FRA, DEU, GRC, HKG, HUN, IND, IRN, IRL, ISR, ITA, JPN, KOR, MEX, NLD, NZL, NOR, PHL, POL, PRT, ROU, SGP, ESP, SWE, TUR, GBR, and USA; (ii) red dots represent BLR, SVK, and VNM; (iii) green dots represent ALB, AZE, CYP, ECU, EST, FJI, GEO, IDN, JOR, KWT, LVA, LTU, LUX, MAC, MYS, MLT, MDA, MNG, MAR, MKD, OMN, SVN, LKA, TUN, URY, PSE; (iv) violet dots represents HRV; (v) country names and codes are found in Appendix A.

Figures 3 and 4 show the ranking of countries in terms of TFP levels in the base and final years (respectively, top 50% and lower 50%). We notice that the USA, the UK, Japan, Germany, France, Italy, and Spain are always in the top ten with the highest TFP level. Moreover, the last ten countries with the lowest TFP level are middle-income or small high-income countries. Furthermore, Croatia, Portugal, Greece, and Philippines regressed in their ranking and dropped from the highest half to the lowest half. In addition, we note a remarkable amelioration (i) within the top pool (Turkey, India and Ireland moved respectively to the 5th, 10th, and 11th ranks), (ii) within the bottom pool (Jordan and West Bank and Gaza gained 10 places), and (iii) between the pools (Belarus, Egypt, Singapore, Slovakia, and Vietnam moved to the top pool). We also find that countries in the lower half are mostly middle-income countries or high-income countries of three categories: (i) small economies, (ii) oil-exporting countries or (iii) ex-communist countries.

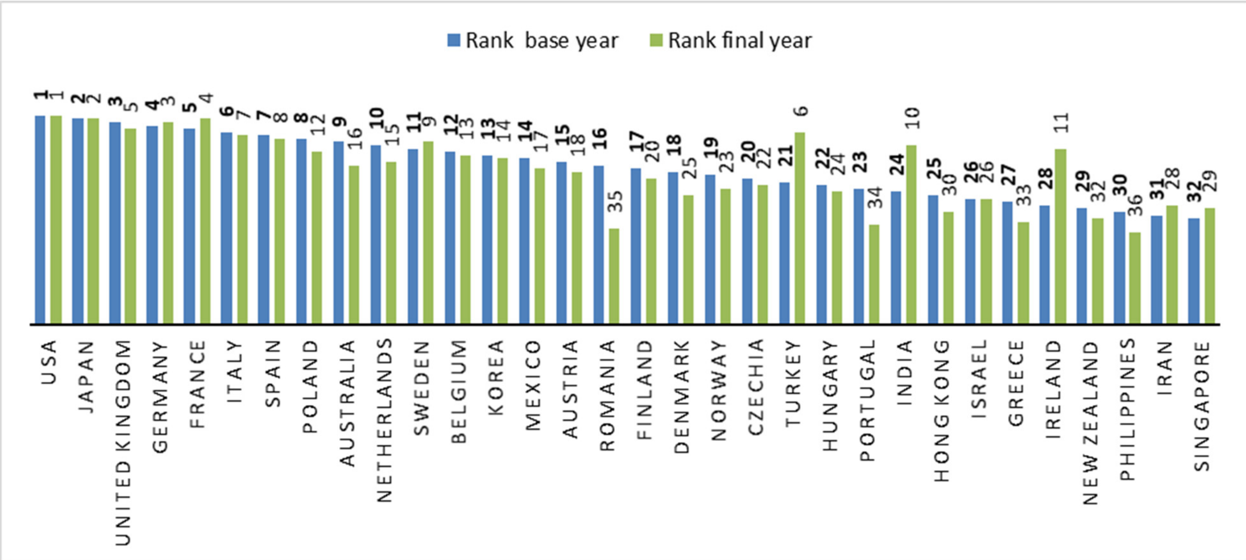


**Figure 3.** Ranking (top 50%).

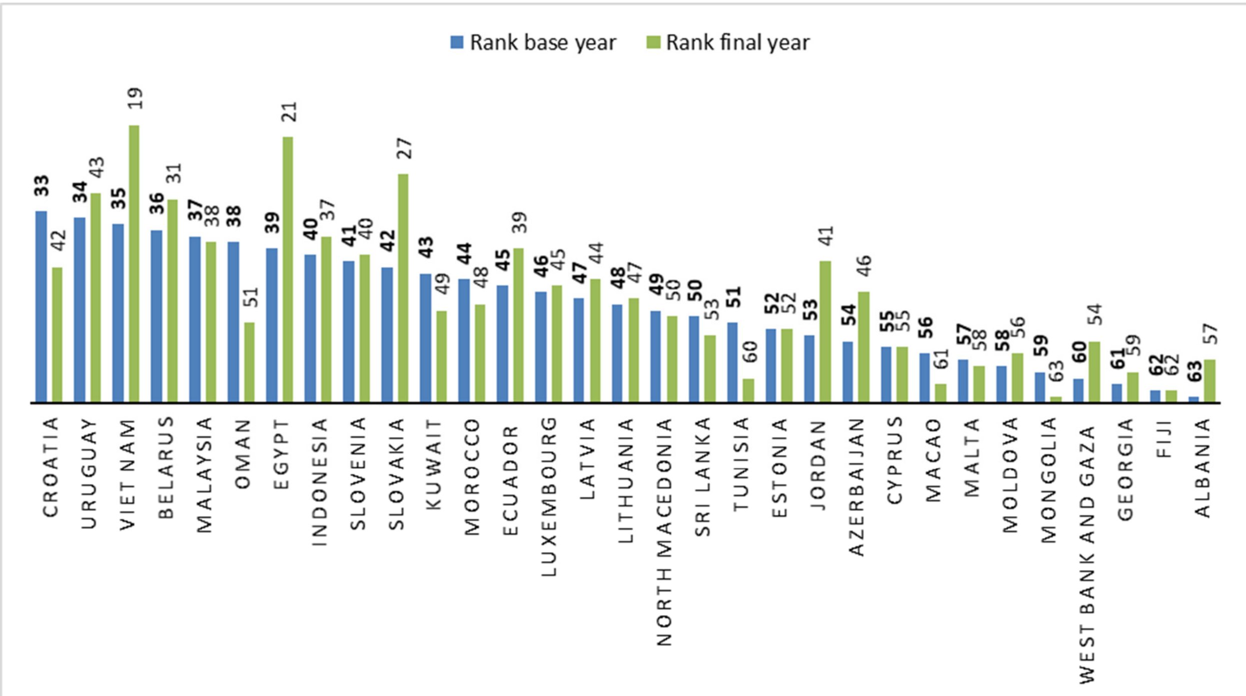


**Figure 4.** Ranking (bottom 50%).

Figure 5 regroups countries into regions (the USA is the leading "region") and shows mean regional TFP levels at base and final years. It shows that ECA region has the second highest average TFP following the USA, while MENA region has the lowest average TFP. Moreover, Asia and LAC regions have quite similar average TFP levels. The decrease in the standard deviation (between the final and base years) reflects a drop in the spread of TFP within each of ECA and LAC regions. The opposite dynamics occurred in the MENA and Asia regions.

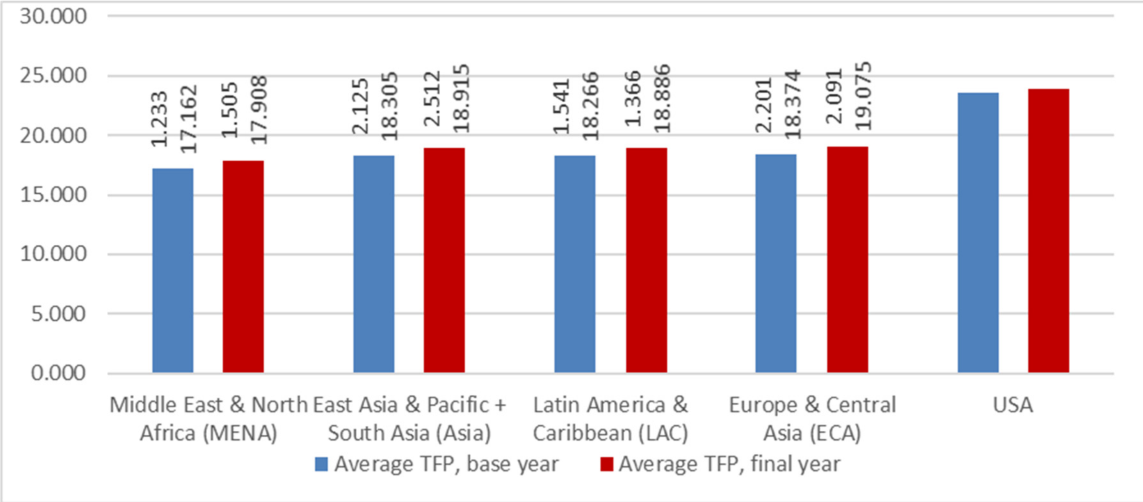


**Figure 5.** Regional mean TFP. Note: Standard deviations (single-digit figures) and TFP values (double-digit figures) are above the bars.

Finally, Figure 6 shows the average TFP per region across the forty years of investigation. This is computed based on member countries' annual average TFP values over the 40-year period. The ranking among regions echoes the one depicted in Figure 5. Moreover, and for all the regions, the average TFP value over the 40-year period is larger than the mean regional TFP in the base year (shown in Figure 5). This shows that all regions have experienced an increase in TFP over the considered period. Figure 6 also shows that the average TFP for high-income countries is higher than that of middle-income countries.

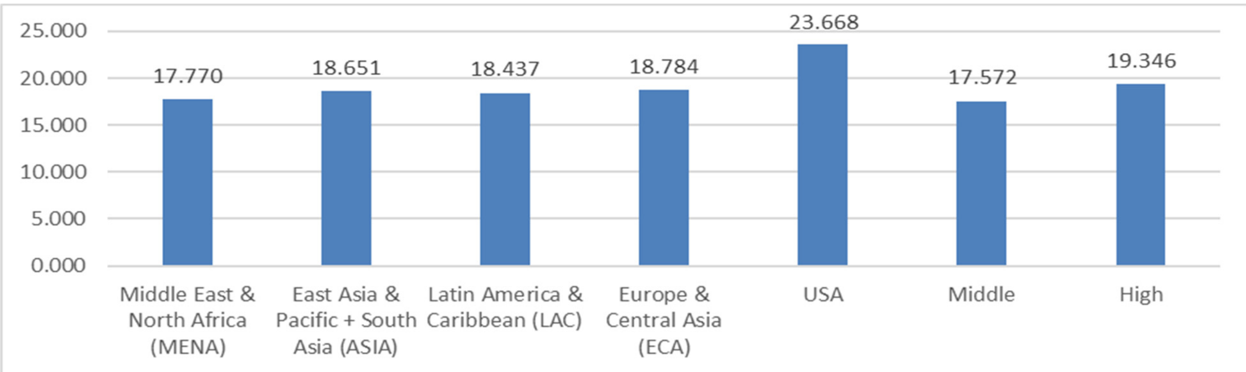


**Figure 6.** Average regional TFP level. Note: Average TFP values are above the bars.

### *5.3. Manufacturing TFP: Intra-Regional Comparison*

Here below we look at the countries' average TFP. We identify the leaders and laggards in each geographic region and, whenever noticeable, we pinpoint countries that made remarkable progress over the period.

Figure 7 shows that the major industrial countries in ECA, namely the UK, Germany, and France, topped the ranking of manufacturing TFP within the bloc. By and large, Western European countries were the best performers. Whereas most of the countries with low TFP levels were either island-countries such as Cyprus and Malta or Eastern European countries. Arguably, the communist heritage of the latter group of countries is a key factor explaining the wedge in TFP levels. The cases of Ireland and Turkey are remarkable with a substantial progress made over the period. Ireland moved from the 21st position in ECA in the base year to the 8th position in the final year. Turkey moved from the 17th position to the third one across the period.

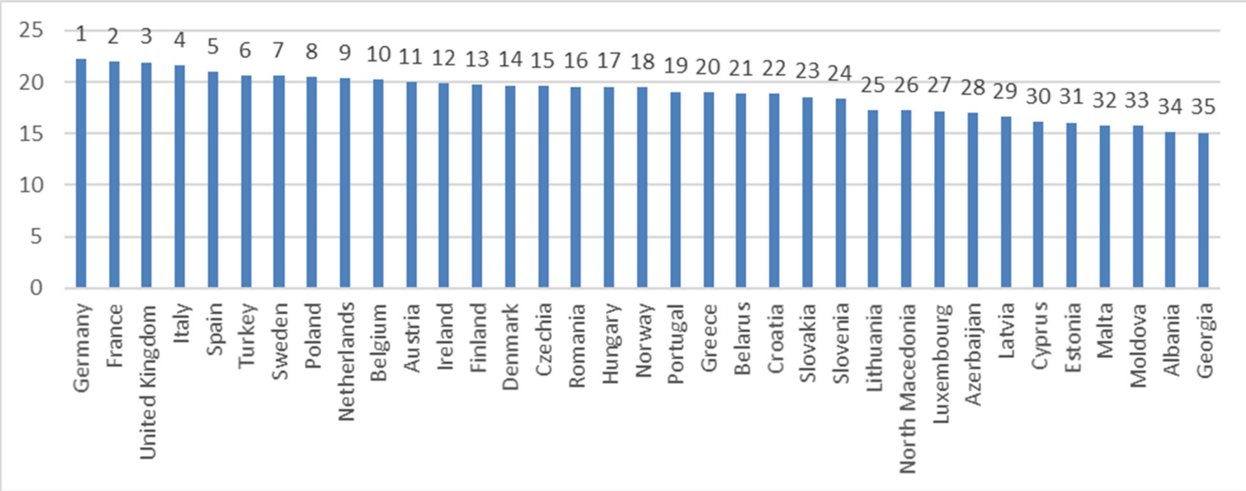


**Figure 7.** Average TFP for ECA countries.

According to Figure 8, Japan, Australia, South Korea—all well-established industrial countries—along with India were the best performers as to manufacturing TFP in Asia. Based on the average TFP ranking, Vietnam is ranked 5th. In fact, a closer comparison between the base year TFP and the final year TFP (not exposed here) shows that a noticeable amelioration in productivity in the manufacturing sector occurred in Vietnam. It moved from the 10th position at the start of the period to the 5th one at the end of it. Two countries, Mongolia and Fiji, in addition to Macao, were at the bottom of the TFP ranking. Mongolia has been traditionally dependent on agriculture and mining, whereas Fiji and Macao are small, mainly tourism-based, economies.

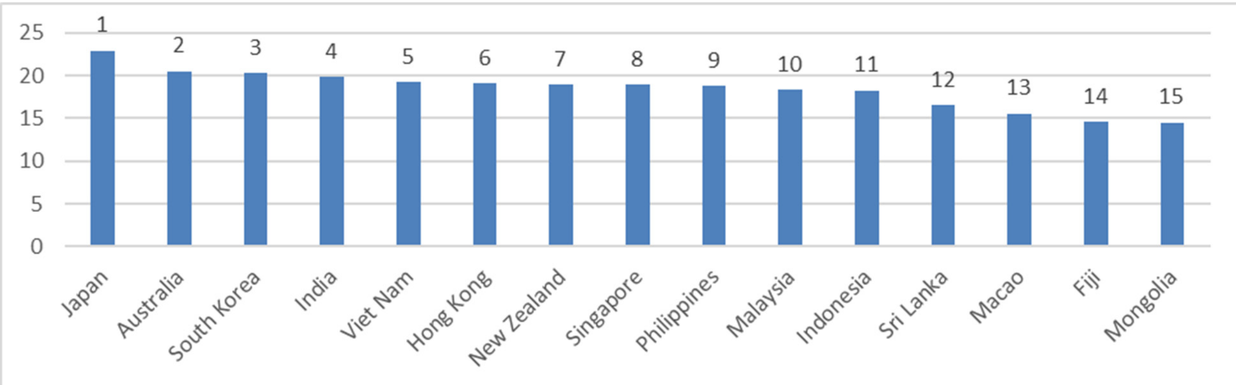


**Figure 8.** Average TFP for Asia countries.

Among the three LAC countries of our sample, Mexico has the leading position (Figure 9). This can reflect its close ties with the US and Canada, notably through the North American Free Trade Agreement (NAFTA) that entered into force in 1994. Indeed, NAFTA was associated with an increase in foreign direct investments in Mexico, a shift of Mexican exports towards manufactured goods, and an improvement in TFP at the industry and firm levels (International Monetary Fund 2004).

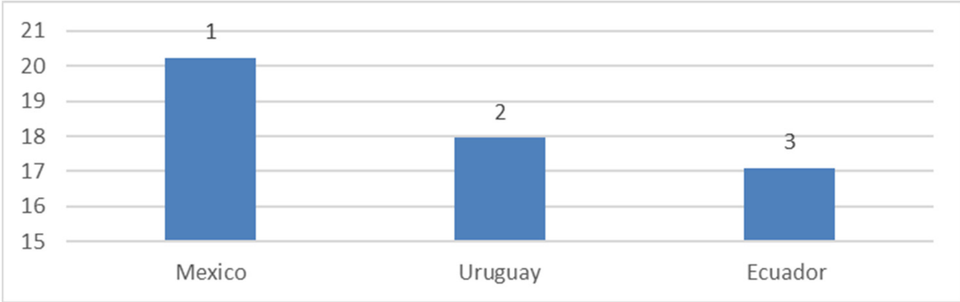


**Figure 9.** Average TFP for LAC countries.

The leaders in the MENA region in terms of productivity in the manufacturing sector are Iran, Israel, and Egypt (Figure 10). Compared to the rest of the region, the three countries are characterized by a large share of the manufacturing sector in the economy. Over the 1980–2020 period, the average share of manufacturing value added in GDP was about 14% in Iran and Israel, and 16% in Egypt[11]. Moreover, across the three countries, there is a vivid relationship between the armed forces and the industrial sector (Mintz 1985; Swed and Butler 2015; Forozan and Shahi 2017; Sayigh 2019; Bahgat and Ehteshami 2021).

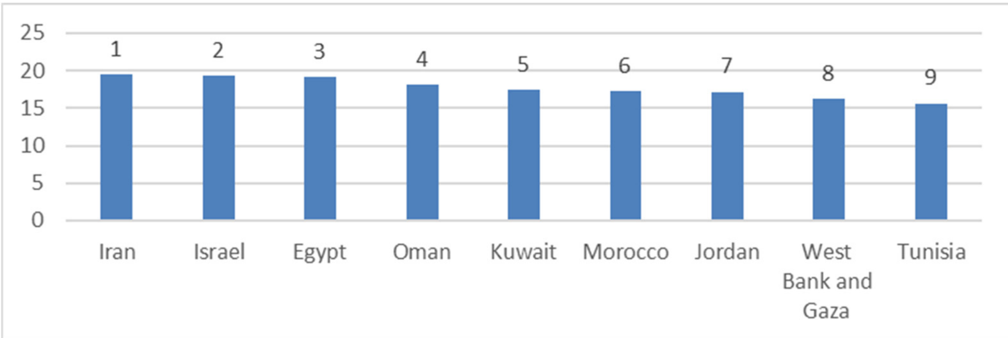


**Figure 10.** Average TFP for MENA countries.

### 5.4. *Manufacturing TFP: Results of the PUR Tests*

Table A4 of Appendix D lays out the results of the three PUR tests that we implemented, while Table 2 presents a summary of the findings.

**Table 2.** Summary of the PUR tests' findings.

| | **Whole Period (1980–2019)** | **Pre-2008 Period (1980–2007)** | **Post-2008 Period (2008–2019)** |
|---|---|---|---|
| Whole sample | Convergence | Convergence | No convergence |
| Asia | Convergence | Convergence | No convergence |
| ECA | Convergence | Convergence | No convergence |

Note: (i) Our 63 sample countries are listed in Appendix A. (ii) "Asia" includes 12 countries: all Asian sample countries except three small economies with a negligible industry: Fiji, Macau, and Mongolia. (iii) "ECA" includes all 35 ECA sample countries. (iv) We did not implement the PUR tests on MENA and LAC regions for two reasons: (a) Their *N* dimension is particularly small (nine and three countries, respectively) which makes the use of the tests unsuitable, and (b) they do not include major industrialized countries as in Asia and ECA. (v) "Convergence" reflects the case where at least two tests indicate a convergence process among some countries; "No convergence" reflects the case where at least two tests indicate the absence of a convergence process among countries.

Table 2 reports summary results of the PUR tests implemented on the entire sample and two regional groupings: Asia and ECA. As noted earlier, the tests are based on the same hypothesis setting, with the rejection of the null implying evidence of a convergence process among some units.

Over the entire period and using our sample of countries, the tests suggest a convergence dynamic occurring among some countries. When applied on each of Asia and ECA along the entire time period, the tests also imply convergence processes among some countries in each grouping. This insinuates that, within each regional group, productivity disparities in the manufacturing sector among countries remained bounded over the covered period.

As aforementioned, common manufacturing TFP experienced an upward trend across the period (Figure 1), with a severe slump in the aftermath of the international financial crisis in 2008. Moreover, as shown in Section 3, the 2008 financial crisis negatively affected the growth in the manufacturing sector. This could have impacted the convergence dynamics in terms of productivity in the manufacturing sector among countries. To examine this possibility, we carried out the tests across two time periods: pre-2008 and post-2008. Regarding the pre 2008 period, the tests point toward a convergence process at play, both in the case of the entire sample and within each of Asia and ECA. As for the post-2008 period, the tests suggest the absence of convergence within the two regional groups as well as among the full sample. Taken together, the findings hint at a possible perturbing effect that the international financial crisis had on the convergence dynamics that was in action among sample countries and within each of Asia and ECA. Arguably, the repercussions of the crisis have reverberated across the economic sectors, including the manufacturing sector, in different ways across countries. The magnitude with which the financial crisis hit the manufacturing sector in each country was largely country specific, reflecting, among other things, the extent to which the country was integrated in the world economy and the degree of intertwining between the manufacturing and financial sectors. Likely, this has led to country-specific implications regarding the post-2008 evolution of TFP in the manufacturing sector, which could explain the break of the convergence process after the 2008 shock.

## 6. Conclusions

Using data on the manufacturing sector from the UNIDO, we generate TFP series for 63 countries over a period of four decades. Following a common routine in the literature, the TFP series are extracted via two steps: We first estimate manufacturing production functions, before deriving the TFP series. Our approach is based on a novel estimation strategy particularly suited for production functions since it (i) is based on country-specific regressions with idiosyncratic coefficients, (ii) allows for a common TFP growth, albeit impacting countries differently, and (iii) accounts for cross-section dependence and nonstationary variables, two data features especially prevalent in macroeconomic series. The generated TFP series are then analyzed extensively across the whole sample of countries and within regional groupings.

The following findings stem from our analysis. First, our results show that common TFP in the manufacturing sector followed a clear upward path over the four-decade period. The major exception was registered in 2008 in the aftermath of the international financial crisis, when common TFP declined severely. Second, countries with the highest manufacturing TFP levels were major developed countries, namely the US, Japan, the UK, Germany, and France. On the other end, most of the countries with a relatively poor performance as to TFP fell in one of three categories: small economies, oil exporting countries, and ex-communist countries. It is also worth noting that several countries managed to climb the productivity ladder with remarkable progress achieved over the period: Vietnam, Ireland, Turkey, India, and Egypt are cases in point. Third, when we compare various regional groupings in terms of mean regional TFP levels, we note the following: (i) All regions have known an increase in their mean TFP level; (ii) the USA was the leading center in terms of manufacturing TFP, followed by European countries; (iii) Asian and Latin American countries had quite similar TFP levels; and (iv) Middle Eastern and North African countries had the lowest productivity levels. Finally, there is evidence of a convergence process in manufacturing TFP that was in action across all sample countries, as well as within each of Asia and ECA. This was brought to a halt after the 2008 shock. To the best of our knowledge, this is the first research that provides a comprehensive analysis of productivity in the manufacturing sector over a relatively large time horizon and for plentiful of countries from different regional groups. The study can be useful to researchers interested in examining manufacturing TFP. Indeed, the descriptive analysis can be the basis of any empirical investigation of TFP in the manufacturing sector. Moreover, the generated TFP series (available in the online resource excel file) can be employed by researchers looking at the determinants of productivity in the manufacturing sector. In addition, policymakers and governmental agencies in charge of the manufacturing sector would also find the analysis useful. They can use the generated series to benchmark their domestic manufacturing sector's TFP against regional and world best performers, and eventually act upon it.

**Author Contributions:** Conceptualization, G.H. and C.B.; Methodology, G.H. and C.B.; Formal analysis, G.H. and C.B.; Investigation, G.H. and C.B.; Writing—original draft, G.H. and C.B.; Writing—review & editing, G.H. and C.B.; Visualization, G.H. and C.B.; Project administration, G.H. and C.B. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** The generated TFP series are available at Zenodo: doi 10.5281/zenodo.7437525.

**Conflicts of Interest:** The authors certify that they have no conflict of interest to declare.

## Appendix A. Sample Countries

| Region | Country/Code |
|---|---|
| Asia | Australia (AUS), Fiji (FIJ), Hong Kong (HKG), India (IND), Indonesia (IDN), Japan (JPN), Macao (MAC), Malaysia (MYS), Mongolia (MNG), New Zealand (NZL), Philippines (PHL), Singapore (SGP), South Korea (KOR), Sri Lanka (LKA), Viet Nam (VNM) |
| Europe and Central Asia (ECA) | Albania (ALB), Austria (AUS), Azerbaijan (AZE), Belarus (BLR), Belgium (BEL), Croatia (HRV), Cyprus (CYP), Czechia (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Georgia (GEO), Germany (DEU), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Malta (MLT), Moldova (MDA), Netherlands (NLD), North Macedonia (MKD), Norway (NOR), Poland (POL), Portugal (PRT), Romania (ROU), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), Turkey (TUR), the United Kingdom (GBR) |
| Latin America and Caribbean (LAC) | Ecuador (ECU), Mexico (MEX), Uruguay (URY) |
| Middle East and North Africa (MENA) | Egypt (EGY), Iran (IRN), Israel (ISR), Jordan (JOR), Kuwait (KWT), Morocco (MAR), Oman (OMN), Tunisia (TUN), West Bank and Gaza (PSE) |
| The USA | the United States of America (USA) |

Note: (i) we followed the classification of the World Bank, with the exception of Malta which we included in ECA and not in the Middle East and North Africa region; (ii) since data on Canada is missing, we considered the US as a region-country.

## Appendix B. Note on Data Collection and Variables Used

The INDSTAT 2 database is available starting 1963. However, we chose 1970 as a starting point of data selection (value added, employment and gross fixed capital formation (GFCF)) given that few countries have data across the three variables before that year.

We then used data on real GFCF to construct capital stocks series, with 1970 being the "initial year". The selection of 1970 as the initial year was handy since it falls considerably behind 1980 (the starting year of our production function estimations). Thus cushioning the repercussions of the initial year stock of capital on the 1980 (and ensuing) capital stock values.

We used the perpetual inventory method (PIM) to construct the capital stock series:

$$k_t = k_{t-1}(1 - depreciation\ rate) + i_t$$

where $k_t$ and $i_t$ are, respectively, the capital stock and the GFCF at year $t$. We adopted a depreciation rate of 15%.

Although several ways have been suggested to compute the initial year capital stock, it is typically a function of initial year investment $(i_0)$ and computed as follows:

$$k_0 = \frac{i_0}{(growth\ rate\ of\ investment + depreciation\ rate)}$$

For most countries the initial year was 1970. For countries with missing 1970 data, the closest year to 1970 was considered as the initial year. We have used the average annual growth rate of GFCF over the first 7 years of available observations as the growth rate of investment. For a number of countries, GFCF series was discontinued between the initial and the last year where GFCF data was available: we interpolated the missing data.

## Appendix C. The Empirical Setting

The approach adopted by Eberhardt and Teal (2020) embraces a broad understanding of TFP: a web of unobserved forces impacting domestic production functions. Such forces enclose three dimensions: (i) cross-country interconnections encompassing economic linkages as well as political and cultural affinities; (ii) universal diffusion of non-rival knowledge, with possibly a differentiated repercussion across countries; and (iii) global shocks affecting all or a subset of countries, albeit to varying degrees.

In view of the complexity of the latent factors driving the TFP, Eberhardt and Teal (2020) adopt an empirical framework couched in a multifactor error setting, with two key relationships. Equation (A1) that represents the production function, where value added in manufacturing sector (in natural logarithm, *ln*) $(y_{it})$ is a function of (i) observable inputs $(x_{cit})$ encompassing labor and capital stock (both expressed in *ln*), and (ii) unobservables $(v_{it})$. Equation (A2) that showcases the latent factors driving the observable inputs. Specifically, for cross-sectional units (countries) $i = 1, \ldots, n$, across time $t = 1, \ldots, T$, and along the two observable inputs (labor and capital) $c = 1,\ 2$, we have:

$$y_{it} = \sum_{c=1}^{2} \beta_i^c x_{cit} + v_{it} \quad v_{it} = \alpha_i + \lambda_i' f_t + e_{it} \tag{A1}$$

$$x_{cit} = \varphi_{ci} + \delta_{ci}' w_t + \varepsilon_{it} \tag{A2}$$

The unobservables in Equation (A1) include a white noise $(e_{it})$ as well as two TFP components: a country-specific effect $(\alpha_i)$, and the TFP evolution $(\lambda_i' f_t)$ embodied by a set of common factors $(f_t)$ with country-specific coefficients $(\lambda_i')$.

Equation (A2) assumes that the observable inputs are affected by a country-specific effect $(\varphi_{ci})$, latent forces $(w_t)$—among which the ones affecting the value added $(f_t)$—and a white noise $(\varepsilon_{it})$.

The framework puts up with the possibility that the latent forces $(f_t,\ w_t)$ evolve in a nonstationary fashion, which accommodates potentially nonstationary value added and inputs. The setup also allows for heterogeneous production functions parameters $(\beta_i^c,\ \alpha_i, \lambda_i')$; it further accommodates the endogeneity of the observable inputs, since they are in part propelled by the same factors affecting the value added $(f_t)$. Lastly, the setting makes room for cross-section dependence via the error term of Equation (A1).

## Appendix D. Data Analysis

**Table A1.** Pesaran (2015) cross-section dependence test.

| | $y$ | $l$ | $k$ | $\widetilde{TFP}_{it}$ |
|---|---|---|---|---|
| CD test | 71.38 | 23.95 | 77.91 | 146.14 |
| $p$-value | 0.00 | 0.00 | 0.00 | 0.00 |

Note: (i) the null hypothesis is weak cross-section dependence, the CD test statistic is normally distributed under the null; (ii) $y$, $l$, and $k$ are in logs.

**Table A2.** Pesaran (2007) panel unit root (CIPS) test.

| $y$ | | | $l$ | | | $k$ | | |
|---|---|---|---|---|---|---|---|---|
| **lags** | **Z [t-bar]** | ***p*-Value** | **lags** | **Z [t-bar]** | ***p*-Value** | **lags** | **Z [t-bar]** | ***p*-Value** |
| 0 | 0.4 | 0.65 | 0 | 1.58 | 0.94 | 0 | −0.35 | 0.36 |
| 1 | 1.24 | 0.89 | 1 | 1.14 | 0.87 | 1 | 1.54 | 0.93 |
| 2 | 2.82 | 0.99 | 2 | 3.49 | 1 | 2 | 3.66 | 1 |
| 3 | 2.94 | 0.99 | 3 | 4.24 | 1 | 3 | 5 | 1 |

Note: (i) the test is based on country-specific augmented Dickey Fuller regressions robust to cross-section correlation (augmentation with lags as mentioned), the null hypothesis is nonstationarity across all panels; (ii) $y$, $l$, and $k$ are in logs.

**Table A3.** AMG estimates of Equation (2).

| **Regressor** | **Estimated Coefficient** |
|---|---|
| $l$ | 0.646 *** (0.07) |
| $k$ | 0.234 *** (0.05) |
| *CDP* | 0.786 *** (0.12) |
| *Country trend* | 0.004 (0.004) |
| *Constant* | 6.709 *** (1.38) |
| Observations | 2119 |
| CD statistic ($p$-value) | 0.828 (0.408) |
| Order of integration | I(0) |
| RMSE | 0.128 |

Note: (i) estimated coefficients are outlier-robust means. (ii) between parentheses standard errors are constructed following Pesaran and Smith (1995) and test the statistical significance of the average coefficient (H0: $\frac{1}{N}\sum_i \hat{\beta}_i = 0$). (iii) *** denotes significance at 1%. (iv) "CD statistic ($p$-value)" refers to the Pesaran (2015) cross section dependence statistic and its corresponding $p$-value, the null hypothesis being weak cross-sectional dependence. (v) "Order of integration" refers to the order of integration of the residuals based on the Pesaran (2007) CIPS test with up to three lags, the null hypothesis being nonstationarity of the residuals, I(0) refers to stationary residuals. (vi) "RMSE" refers to the root mean square error. (vii) $l$ and $k$ are in logs.

**Table A4.** PUR tests results.

| | | **Whole Sample** | **Asia** | **ECA** |
|---|---|---|---|---|
| Entire period (1980–2019) | IPS | No convergence | Convergence | No convergence |
| | MW | Convergence | Convergence | Convergence |
| | PP | Convergence | Convergence | Convergence |
| Pre 2008 period | IPS | - | Convergence | - |
| | MW | Convergence | Convergence | Convergence |
| | PP | Convergence | Convergence | Convergence |

**Table A4.** *Cont.*

| | | **Whole Sample** | **Asia** | **ECA** |
|---|---|---|---|---|
| Post 2008 period | IPS | No convergence | No convergence | No convergence |
| | MW | Inconclusive | No convergence | Convergence |
| | PP | No convergence | No convergence | No convergence |

Note: (i) the IPS test is implemented on Equation (7) augmented with lags of the dependent variable to purge serial correlation, the number of lags is chosen to minimize the Akaike information criterion subject to a maximum of 5 lags, the IPS test statistic is $W_{t\text{-}bar}$. (ii) the MW test is implemented on Equation (7) augmented with (up to 5) lags of the dependent variable to purge serial correlation, the MW test statistic is the inverse $\chi^2$ $P$. (iii) the PP test is implemented on Equation (7), we allowed (up to 5) Newey-West lags to purge serial correlation, the PP test statistic is the inverse $\chi^2$ $P$. (iv) across all tests we subtracted cross-sectional averages from $\Delta\widetilde{TFP}_{it}$ to account for the impact of cross-section dependence in the $\widetilde{TFP}_{it}$ series. (v) "Convergence": evidence of convergence across all/most of the lags, "No convergence": evidence of no convergence across all/most of the lags, "Inconclusive": contradictory results across lags, "-": insufficient observations to apply the test. (vi) "whole sample" refers to our 63 sample countries that are listed in Appendix A, "Asia" includes 12 countries: all Asian sample countries except 3 small economies with a negligible industry: Fiji, Macau and Mongolia, "ECA" includes all 35 ECA sample countries.


**Figure A1.** TFP evolution, by country.

## Notes

1 The sample countries are listed in Appendix A.

2 Throughout the analysis we follow the World Bank's regional classification with one exception: we consider Malta as part of ECA and not of MENA. This is essentially motivated by the fact that Malta is an EU member country.

3 The average share of services' value added in GDP in the USA was around 75% over the covered period. The average share of fuel exports in total merchandise exports was nearly 33.7% for the MENA region across the period. We computed the averages based on the World Bank's WDI database.

4 Our sample of 63 countries consists of 39 high-income countries and 24 middle-income countries, based on the World Bank classification.

5 Details about the methodology are found in Appendix C.

[6] Eberhardt and Bond (2009) showed that the AMG estimator yields unbiased estimates under numerous setups and does not suffer from the standard concerns related to the use of estimated regressors from a first-stage regression.

[7] The choice of the tests was primarily dictated by the fact that our dataset is unbalanced with a number of countries having missing observations across a large number of years. The three tests are the ones that are applicable in this context. Moreover, the dimensions of our dataset (moderate $N$, large $T$) make the tests particularly appropriate.

[8] We use weighted averages instead of simple ones to account for the large disparities that exist among sample countries in terms of data availability.

[9] Upon checking the $\widetilde{TFP}$ series, we found that for most of the countries the series does not exhibit any trend.

[10] Details about the variables and data used are found in Appendix B.

[11] The World Bank, WDI database.

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