IARIW 2021

Monday 23 – Friday 27 August

Productivity Growth & Global Slowdown: Insights from Emerging Markets & Developing Economies and Advanced Economies

Abdul Azeez Erumban

(University of Groningen)

Deb Kusum Das

(University of Delhi)

Samiran Dutta

(Paris School of Economics)

Paper prepared for the 36th IARIW Virtual General Conference
August 23-27, 2021
Session 7: Economic Growth and Productivity with Special Emphasis on Developing Economies I
Time: Tuesday, August 24, 2021 [16:30-18:30 CEST]

Productivity Growth & Global Slowdown: Insights from Emerging Markets & Developing Economies and Advanced Economies

Abdul Azeez Erumban
Faculty of Economics and Business
University of Groningen, Netherlands

Deb Kusum Das*
Department of Economics
Ramjas College, University of Delhi, India

Samiran Dutta
Incoming MRes Economics Candidate
Paris School of Economics, Paris

Abstract

The impact of global financial crisis across the world has engaged the attention of both academics and policy makers. In recent times, the global productivity slowdown across the world has occupied a center stage as labor productivity decline impact both growth and livelihoods. The past decades have seen a remarkable drop in the productivity growth rates for many advanced economies, there remains less evidence on what happened in emerging markets and developing economies and if they any correlation with the global recession in 2008. Against this, the present paper attempts to examine the impact of global slowdown on labor productivity growth on a panel of economies comprising both advanced countries and the group of emerging markets and developing economies. The period covered is from 1995-2020 and using a correlated random effects model, the paper offers several interesting findings. First, capital deepening emerges as a strong factor in explaining the observed productivity growth across the entire panel of countries. The role of employment and labor quality are as expected. In addition, it is seen that good governance, globalization and higher life expectancy are also important in observed labor productivity dynamics. Our paper concludes that the decline in labor productivity due to global slowdown as witnessed most advanced nations is not so pronounced in emerging markets and developing economies.

JEL Classification: E24**,** F62, O47, O57

Keywords: Aggregate Labor Productivity, Economic Growth, Globalization, Developing Countries.

August 2021

Paper prepared for the 36th IARIW general conference being organized by Statistics Norway at OSLO virtually on August 23-27, 2021. The second author would like to thank IARIW for support to participate at the 36th general conference, being held virtually at Oslo. The usual disclaimers apply.
**Corresponding author: dkdas@ramjas.du.ac.in*

1. Introduction

Labor productivity growth is widely seen as a yardstick of economic growth and welfare across the global world encompassing emerging markets, developing as well as advanced economies. Further, the ongoing low productivity growth across the global world continues to attract attention more so in current times. A recent study by Goldin *et al.* (2021) asserts that for advanced economies, two things emerge - first, there was no convergence in the 1995-2005 decade, so slower convergence cannot explain the slower rates in Europe after 2005 compared to 1995-2005. Second, while it is true that the frontier (US) may be returning to "normal" rates of growth post 2005 IT boom, but growth remains low across the advanced nations. It is not surprising therefore to find that the multifactor productivity continues to decline and fall to near zero for advanced economies on one hand and on the other economies like China, India, Brazil, Mexico experiencing smaller decline in the their productivity especially in the post slowdown period.

Several possible determinants of this observed slowdown are being suggested ranging from mismeasurement (Byrne *et al.* 2016; Syverson, 2017), structural change (Baily & Montalbano 2016; Gordon & Sayed, 2019), impact of capital stock (Goodridge *et al.*, 2016), one-off effects (Gordon 2016; Gordon & Sayed 2019), technology lags (Brynjolfsson *et al.*, 2021). In addition, aspects such as firm level dynamics (Bartelsman & Doms, 2000; Syverson, 2011), the role of intangible assets (Corrado *et al.*, 2009), and recognition of the role of trade and globalization seems to emerge as possible theories that need exploration for our understanding of the productivity slowdown and its associated dynamics.[1]

Though the focus of the productivity slowdown continues to engage with advanced economies, it is important to understand that emerging markets as well as developing economies accounted for a large share of the global growth since 2000. A recent paper by Gregorio (2018) points out that productivity growth in emerging markets is correlated to the growth performances of the advanced economies notably US. Therefore, it becomes important to assess the impact of the global slowdown on the advanced economies in order to understand the dynamics in play in these emerging markets. In addition several interesting facts emerge out of a study by Dieppe (2020) that convergence of emerging market and developing economies (EMDEs) to advanced economy remains a challenge not only because of slowdown in labor productivity

[1] Goldin *et al.* (2021) presents a detailed review.

growth post 2008 global crisis but likely to be further aggravated by recession triggered by the COVID-19 pandemic. This may happen through lower investments, erosion of human capital due to job losses as well as schooling loses accompanied by trade and supply chain disruptions[2].

The motivation of this paper emerges from the fact that the global economy has seen downturn in productivity growth in the recent years. Indeed, the global financial crisis might have aggravated the productivity slowdown, but the decline started even before the onset of the crisis (Ramskloger, 2015; Van Ark and Jaeger 2017; Erumban and van Ark 2018). Hence, there emerged a debate on whether the world is seeing the end of massive productivity improvements.[3] This paper is an attempt to understand productivity dynamics in emerging markets and developing economies alongside the advanced countries. In particular, we undertake an examination of the labor productivity growth performance for panel of economies encompassing emerging markets and developing economies and advanced economies for the period 1995-2020 and compare the pre global slowdown period (1995-2007) with the post crisis period (2008-2020) with detailed quantitative rigors. Using The Conference Board (TCB) dataset, which provides detailed data country information on crucial economic variables of concern. Using panel econometric analysis, the paper helps us ascertain if the productivity slowdown is evident for the group of emerging markets and developing economies alongside advanced countries. Our findings show that capital deepening is a significant factor in the observed productivity growth across all economies leaving behind possible roles of employment or labor quality. We conclude by arguing that the impact of global crisis on declining productivity is less for emerging markets and developing economies in contrast to advanced economies where the impact of the crisis on productivity decline is stronger.

The paper is structured as follows- Section 2 outlines the global productivity slowdown. The methodology and dataset are formulated in section 3. The empirical findings are presented in section 4. The final section concludes the paper.

---

[2] Refer to van Ark *et al.* (2021).

[3] The discourse has centered on two views- (1) the importance of general purpose technologies – in particular electricity and information and communication technology (ICT) – demography, education, inequality, globalization, environment and debt on understanding growth and productivity (See Gordan, 2016; Brynjolfsson and McAfee, 2011) and (2) secular stagnation, where advanced economies are entering into a long-term productivity stagnation due to multiple factors (Summers, 2014 versus Eichengreen, 2015).

2. Global Productivity Slowdown

The onset of information and communication technologies, the rapid spread of globalization, and the participation of several emerging market economies in the global value chain were essential factors that changed the course of global economic and productivity growth during the last few decades. During the 2000-2017 period, *i.e.*, prior to the global financial crisis, the global per capita income grew at an annual rate of 3.2 percent, helping many poorer nations improve their standard of living. However, in the post-crisis years since 2012, the rate of growth fell substantially to 2 percent, putting breaks on the pace of the improvements in per capita income. This fall in income growth was driven by erosion in productivity growth in the global economy both in advanced and emerging market economies. In fact, many previous researchers have documented that the productivity slowdown in countries like the US started even earlier than the financial crisis, and the reasons are more than the crisis per se (Decker *et al.*, 2017; van Ark *et al.*, 2016; Syverson, 2017; Crafts, 2018).

Figure 1 shows the global economy's annual GDP and labor productivity growth rates from 1998 to 2019. The global growth is obtained as a weighted average of 128 individual economies consisting of 92 emerging markets and 36 advanced economies. The weights are their relative size in the global nominal GDP. The difference between the two lines on the chart is the global employment growth, which is generally positive during this period, except in 2009. The figure shows that during the 2000-2007 period - the pre-global financial crisis period- global GDP and productivity increased rapidly. This was also the period that witnessed China's entry into the WTO and the faster expansion of the global manufacturing value chain, and faster growth in other large emerging markets such as India (Wu et.al., 2017). However, following a rapid fall during the crisis years 2008 and 2009 and an immediate post-crisis recovery in 2010, the productivity growth rate shows a falling trend, with only moderate improvements in a few years. On average, the labor productivity growth fell from 2.7 percent during 2000-2007 to 1.6 percent from 2012-2019 - almost a full percentage point decline.

The remarkable growth experience of the global productivity in the pre-crisis years has ended around the late 2000s, and the recent Covid-19 pandemic may have affected the productivity trend. There are multiple explanations available in the literature on what caused the global productivity slowdown. For instance, Crafts (2018) puts forward a set of explanations drawn from the literature. Erumban and van Ark (2018) also provide a list of explanations identified by previous literature, which are discussed briefly below.

Figure 1: Growth rate of GDP and labor productivity, Global Economy, 1995-2019

Source: The Conference Board Total Economy Database
Notes: Growth rates are log changes. Global aggregate is arrived at using nominal GDP weights, all measured in PPP terms.

The global financial crisis has played an important role in changing the course of productivity trends. As is clear from Figure 1, the fall in global production was larger than the fall in jobs during the global financial crisis. This happens as firms cut production during a recession while still keep their resources, expecting a sooner recovery. The recovery, however, can take longer in reality (see Reinhart and Rogoff, 2014), causing a direct effect on productivity growth. Moreover, the worsened credit conditions after the financial crisis may have weakened investment expansions and new entry of firms, lowering competition and productivity growth in the advanced economies indirectly. Indisputably, the crisis significantly impacted global productivity, although one might argue that it is likely temporary (see Crafts, 2018).

A second explanation that the literature identifies is the slow pace of technology translating into productivity growth. For instance, Gordon (2016) maintains that the productivity surge in the late 1990s and early 2000s, which can be largely attributed to the ICT revolution, has ended. The pace of technology has moved to its natural path, which is slow. Along with the increased skill content of new technologies, it makes the adoption of technologies and the speed at which they translate into productivity slow. In contrast, Brynjolfsson and McAfee (2011) argue that this slowdown in the pace of technology is only temporary, and the productivity effect of the current technological change will come in with a lag (also see Crafts, 2018). We have seen a similar lag in the case of ICT in the 1990s. van Ark *et al.* (2016) also maintains that the productivity impact of many new technologies is likely to come once we pass the installation phase to diffusion and deployment phases. In either case, the current slowdown in global productivity may have some relationship with the slow pace of technology diffusion and its productivity pay-offs.

Summers (2014) provides the secular stagnation explanation related to the slowdown in consumption and investment in tangible and intangible assets and human capital. The slowing labor supply and low inflation in the advanced economies provide little incentive to firms to make new investments to boost productivity, making advanced economies enter into long-term stagnation.

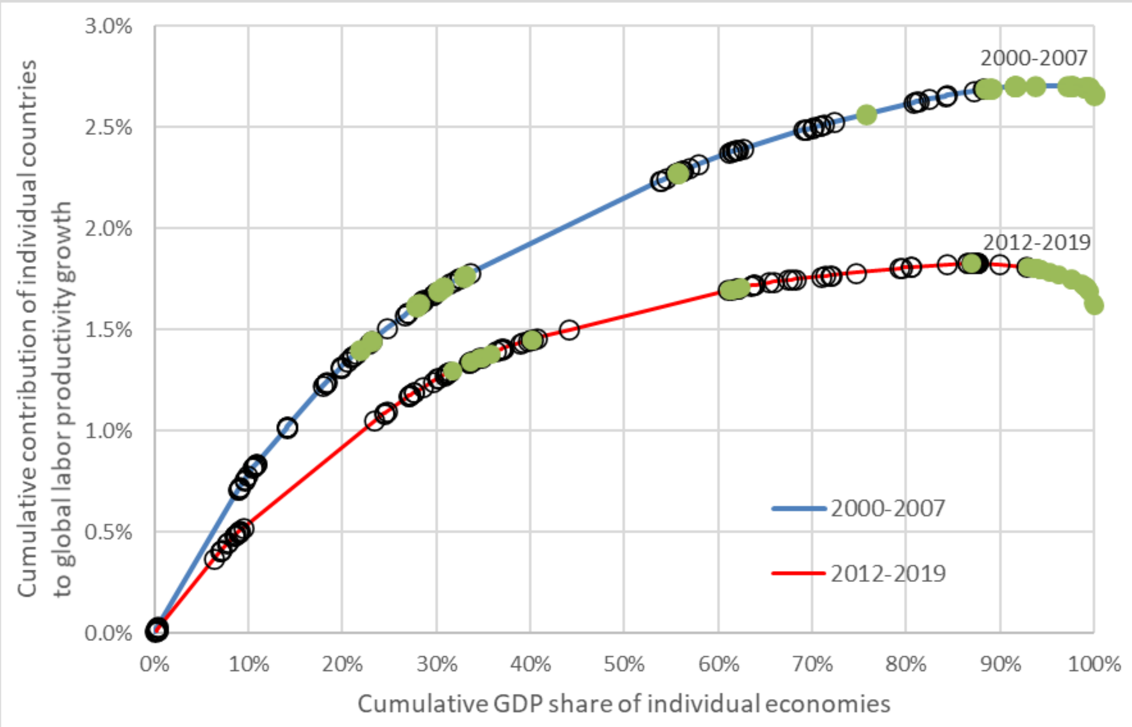
Two other explanations summarized in Erumban and van Ark (2018) are related to policy and regulatory environment and measurement issues (also see Crafts, 2018, and Syverson, 2017). The first is regarding several reforms, such as financial sector reforms in the United States after the global financial crisis, which limited bank's ability to lend new investment projects, the lack of a single market for goods and services in the European Union, several cybersecurity regulations, and rigid labor market practices. The second is regarding the failure of national accounts in measuring the increasing share of digital transactions in the economy, which has significant welfare and productivity impacts. Although the measurement issues are important, it is hard to attribute all the productivity slowdown to measurement issues per se. For instance, Syverson (2017) considers the role of measurement issues in accurately measuring US productivity and concludes that the case for mismeasurement hypothesis has some hurdles when confronted with the data.

A final point, which is given less attention in the literature, is the role of emerging markets. Several emerging market economies had substantial productivity growth - thanks to their pace of catch-up with the frontier - in the 2000s, which seem to have lowered in recent years, especially after the global financial crisis. A number of reasons, other than the global reasons explained above, might be playing a role here, including domestic changes in large emerging markets like China. For instance, China has been moving away from an investment-manufacturing-export-led economy to a more consumer-service-domestic oriented economy, which is entailed to have lower productivity growth. Moreover, the fall in global trade intensity lowered the production and productivity of manufacturing, particularly intermediate goods manufacturing. Reasons for the fall in trade intensity ranges from changing consumption and production composition globally, and in large emerging markets such as China, in particular, falling pace of globalization amid rising nationalistic rhetoric in many advanced economies and the rising consolidation of global production chains (*e.g.*, Timmer *et al.*, 2016).

In Figure 2, we depict the cumulative share of individual economies in global GDP on the X-axis and their cumulative contribution to global labor productivity growth - the so-called Harberger diagram. The black circles are individual emerging market economies, and the green ones are advanced economies. The fall in productivity growth in the post-crisis years is visible across the board, both in emerging and advanced economies. Yet, there was a difference. Although the growth rate fell in the emerging market economies, as shown in Figure 2, many advanced economies witnessed a deceleration in productivity growth in the post-crisis years. We see that both groups of countries were generally witnessing an increase in productivity growth during the 2000-2007 period, while in the post-crisis period, the rate of growth declined everywhere. However, it still continued to grow positively in most emerging market economies. In contrast, several advanced economies show a fall in productivity, as is revealed by the green circles at the extreme right part of the 2012-2019 line. The black circles in the figure, which are the emerging markets, constituted 43 percent of global GDP in the pre-crisis period, which increased to 53 percent in the post-crisis period. At the same time, their relative contribution to global labor productivity growth increased from 63 to 77 percent. Moreover, although in absolute terms, the productivity contributions fell in both advanced and emerging market economies, the magnitude of the decline was more intense in the developed economies than in the emerging ones. Obviously, the global slowdown is not an advanced economies phenomenon, but the pace of productivity decline in the advanced world appears to be more damaging and acute compared to that of the emerging economies.

This fall was visible across the board, both in emerging and advanced economies (Figure 2). Yet, there was a difference. Although the growth rate fell in the emerging market economies, as shown in Figure 2, many advanced economies witnessed a deceleration in productivity growth. Figure 2 depicts the cumulative share of individual economies in global GDP on the X-axis and their cumulative contribution to global labor productivity growth - the so-called Harberger diagram. The black circles are individual emerging market economies, and the green ones are advanced economies. We see that both groups of countries were generally witnessing an increase in productivity growth during the 2000-2007 period, while in the post-crisis period,

Figure 2: Growth rate of GDP and labor productivity, Global Economy, 1998-2019



Source: The Conference Board Total Economy Database
Notes: Growth rates are log changes. Global aggregate is arrived at using nominal GDP weights, all measured in PPP terms.

the rate of growth declined everywhere. However, it still continued to grow positively in most emerging market economies. In contrast, several advanced economies show a fall in productivity, as is revealed by the green circles at the extreme right part of the 2012-2019 line. The black circles in the figure, which are the emerging markets, constituted 43 percent of global GDP in the pre-crisis period, which increased to 53 percent in the post-crisis period. At the same time, their relative contribution to global labor productivity growth increased from 63 to 77 percent. Moreover, although in absolute terms, the productivity contributions fell in both advanced and emerging market economies, the magnitude of the decline was more intense in the developed economies than in the emerging ones. The rest of this paper delves deeply into this issue. It examines econometrically whether the post-crisis productivity decline was significantly more intense in the advanced economies than emerging and developing ones, even after controlling for various other factors that could affect productivity growth.

3. Methodology & Database

3.1. Production Function Framework

The analysis in this paper is conducted at the aggregate economy level, using aggregate GDP data, and therefore, our econometric approach assumes the existence of an aggregate production function. The basic data on GDP and factor inputs (capital and labor) used in the study are obtained from the Conference Board Total Economy Database (TED). We begin with a standard Cobb-Douglas production function in a log functional form:

$$\ln Y_t = \ln A_t + \beta_K \ln K_t + \beta_L \ln L_t \tag{1}$$

where Y denotes GDP, K is the capital input, and L is labor input, all for year t. The TED measures capital and labor input as capital services and labor services, respectively. Which leads to the following decomposition:

$$K_t = S_t . Q_t^s \tag{2}$$

$$L_t = H_t . Q_t^H \tag{3}$$

In equation (2), S_t is the stock of aggregate capital (a summation of ICT capital stock (S_t^{ICT}) and non-ICT capital stock (S_t^{nICT})) and Q_t^s is the capital composition index. In equation (3), H_t denotes total employment and Q_t^H is the labor composition index. The labor and capital composition index measure the changes in the composition of these inputs towards high-skilled workers and high productivity assets (*e.g.*, ICT), respectively. These equations allow us to rewrite equation (1) as:

$$\ln Y_t = \ln A_t + \beta_K \ln(S_t . Q_t^s) + \beta_L \ln(H_t . Q_t^H) \tag{4}$$

Subtracting the natural log of employment ($\ln H_t$), and combining capital quantity and composition into one single input as in (1), we obtain the labor productivity version of the above equation, which can be expressed as:

$$\ln y_t = \ln A_t + \beta_K \ln K_t + \beta_L \ln Q_t^H + (\beta_L - 1) \ln H_t \tag{5}$$

where $y_t = Y_t / H_t$ denotes output per employed persons. Under the assumption of constant returns to scale, *i.e.*, when we assume $\beta_K + \beta_L = 1$, equation (5) turns into the standard growth accounting decomposition of labor productivity growth:

$$\ln y_t = \ln A_t + \beta_K \ln k_t + \beta_L \ln Q_t^H \tag{6}$$

where $k_t = K_t / H_t$. Equation (6) is the basic model that we use in this paper. However, to maintain generality, we do not impose the assumption of constant returns to scale, and hence rely on equation (5). Moreover, we extend the model to include additional explanatory variables that can affect labor productivity beyond capital and labor inputs. Since TFP is a residual in equation (5), these control variables may be considered indicators that indirectly influence labor productivity through TFP. Thus, our skeletal regression model can be expressed as:

$$\ln y_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_Q \ln Q_{it}^H + \beta_H \ln H_{it} + \sum_{i=1}^{n} \beta_i X_{it} + \omega_i + \varepsilon_{it} \tag{7}$$

where β_Q is same as β_L in the previous equations, and β_H is equivalent to $(\beta_L - 1)$ in equation (6). X_i represent the set of control variables, ω_i is the time invariant error and ε_{it} is the residual error term. Since the purpose of this study is to analyze the labor productivity dynamics of the Global Financial Crisis (GFC) across the two groups of countries, namely – "Emerging & Developing Economies (EDE)" and "Advanced Economies (AE)", dummy variables are added to the model in the following manner:

$$\begin{aligned} \ln y_{it} = \beta_0 + \beta_K \ln k_{it} + \beta_Q \ln Q_{it}^H + \beta_H \ln H_{it} + \sum_{i=1}^{n} \beta_i X_{it} + \beta_{ed} D_{ed} + \beta_{pc} D_{pc} \\ + \beta_{in} (D_{ed} \cdot D_{pc}) + \omega_i + \varepsilon_{it} \end{aligned} \tag{8}$$

where the dummy variables are defined as follows:

$$D_{ed} = \begin{cases} 1, & for\ Emerging\ and\ Developing\ Economies \\ 0, & for\ Advanced\ Economies \end{cases} \tag{9}$$

$$D_{pc} = \begin{cases} 1, & for\ post\ crisis\ (post\ 2008)\ years \\ 0, & otherwise \end{cases} \tag{10}$$

and $D_{ed} \cdot D_{pc}$ is the interaction dummy, which is defined analogously from the definitions of D_{ed} and D_{pc} – it takes a value one for post-2008 years for EDE's and zero otherwise. From equation (8), we can interpret the following – if $\beta_{ed} > 0$, then the predicted labor productivity growth of EDE's was higher relative to AE's from 1995-2020; if $\beta_{pc} < 0$, then we observe a post-2008 slowdown in predicted labor productivity growth; and finally, if $\beta_{in} > 0$, we can conclude that the impact of crisis on reducing productivity is lower in EDE's as compared to AE's.

3.2. Correlated Random Effects (CRE) Model

It is well known that the FE approach is usually more convincing than the RE approach when the analysis is based on aggregate data, since the data cannot be thought of as a random sample from a larger population and the explanatory variables of interest are not set experimentally. In such cases, the time invariant cross-sectional characteristics cannot be thought of as independent to the regressors. Since FE allows for arbitrary correlation between such cross-sectional characteristics and the regressors, it is preferred for policy analysis using aggregate data. However, the FE approach is unable to estimate the partial effect of time-invariant regressors due to its process of time-demeaning variables before running the regression. This means that the coefficient β_{ed} of the group dummy (D_{ed}) cannot be estimated using FE. On the other hand, the RE approach can provide coefficient estimates such time-constant variables, but it suffers from the exogeneity assumption with time-invariant cross-sectional characteristics. Given such theoretical limitations of the RE and FE approaches, we utilize an alternative model.

To estimate the regression equation specified in (8), we use a Correlated Random Effects (CRE) model (see Wooldridge, 2010). This approach is taken due to four main reasons. First, the model allows us to estimate the time invariant group dummy variable (D_{ed}), which cannot be estimated directly from FE estimation.[4] Second, the CRE model allows us to model the correlation between the time invariant error term (ω_i) and the time varying explanatory variables rather than assuming no correlation (the Random Effects approach) or removing the time invariant error by time demeaning all the variables (the Fixed Effects approach). Third, the estimation of the CRE model allows hypothesis testing which provides a regression based robust Hausman test to choose between the Fixed Effects (FE) and Random Effects (RE) estimates. Fourth, the CRE model by construction controls for the average level of given time-varying explanatory variables whilst estimating the partial effect of that variable on the dependent variable of interest – thus the partial effect accounts for systematically higher/lower differences of the explanatory variable for difference countries.

[4] It is known that the FE estimation demeans each variable in order to remove the time invariant error term. Since the value of D_{ed} does not change over time, FE estimation will simply remove such an time invariant variable.

This approach assumes a linear relationship between the time invariant error (ω_i) and time average of the j^{th} time-varying explanatory variable ($\overline{Z}_{j,i} = t^{-1}\sum_{t=1}^{T} Z_{j,it}$), such that:

$$\omega_i = \omega + \sum_{j=1}^{n} \psi_j \overline{Z}_{i,j} + r_i \qquad (11)$$

where $i = 1, 2, .., n$ represents the cross-sectional units. Importantly, in the above equation:

$$cov\big(\,\overline{Z}_i, r_i\big) = 0 \quad \forall i = 1,2, .. n \qquad (12)$$

This is because by assumption all Z_{it} are uncorrelated with r_i and $\overline{Z}_i$ is just a linear function of a particular Z_{it}. The inclusion of equation (11) augments equation (8) in the following manner (with Z consisting of labor, capital and all control variables):

$$\ln y_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j Z_{j,it} + \sum_{j=1}^{n} \psi_j \overline{Z}_{j,i} + \beta_{ed} D_{ed} + \beta_{pc} D_{pc} + \beta_{in}\big(D_{ed} D_{pc}\big) + r_i + \varepsilon_{it} \qquad (12)$$

Where $Z_{j,it}$ represents the time varying explanatory variables and β_j are their corresponding coefficients. Thus, $\overline{Z}_{j,i}$ represents the time averages of each *j* time varying explanatory variable, where the mean values are taken for the respective cross-sectional unit.[5] Importantly, it should me mentioned that we do not include the time averages of the dummy variables D_{pc} and $D_{ed} D_{pc}$, since the time averages of these variables will just add constants[6] to equation (12), which need not be done since we already have an intercept. The CRE model in equation (12) is then estimated using RE, where $\overline{Z}_{j,i}$ controls for the possible correlation between the j^{th} time varying explanatory variables and the time invariant error (ω_i), the remaining error r_i is uncorrelated with all $Z_{j,it}$ ($j = 1, 2, .., n$).

The RE-GLS estimation of equation (12) leads to (see Wooldridge, 2010):

$\hat{\beta}_{j,CRE} = \hat{\beta}_{j,FE}$ for all *j* time-varying explanatory variables (13)

This means that adding the time averages of such variables essentially leads to coefficient estimates that are identical (or close to) the estimates that we would obtain by simply running

[5] This means we takes the time average of j^{th} time-varying explanatory variable $x_{j,it}$ for each i^{th} cross-sectional unit. For example, we take the mean values of the capital deepening variable ($\ln k_{it}$) for each country i, leading to a series of mean values ($\overline{\ln k_{it}}$) for all i countries and this is repeated for all *j* time-varying explanatory variables.
[6] This is true because the mean value of these time dummy variables will simply be $\frac{1}{T}$, since the value of zero for these dummy variables will not add anything to equation (12).

a FE estimation of equation (8). This analytical result leads to the robust Hausman test since in the following manner – plugging in $\psi_j = 0$ ($\forall j = 1, 2, .., n$) in equation (12) and running a RE estimation will lead to the usual RE estimates ($\hat{\beta}_{j,RE}$). Thus, we can run a standard hypothesis test:

$H_o: \psi_j = 0$ against the two-sided alternative $H_a: \psi_j \neq 0$ (14)

and check for significant results from the computed p-values. If the null is rejected, the RE approach is rejected in favor of the FE approach. The robustness of this test arises from the implementation of clustered standard errors[7] during the RE estimation of equation (12). The inference is thus made robust to the presence of heteroskedasticity, while Generalized Least Squares (GLS) approach in RE estimation of equation (12) takes care of serial correlation.

3.3. Dataset

We rely on the latest version of Total Economy Database™ (TED) data published by The Conference Board for our basic variables – GDP and factor inputs. TED provides a comprehensive panel dataset for 131 countries for the time period 1995-2020, covering variables such as output, capital stock (ICT and non-ICT), capital composition index, employment and labor quality index among others. To distinguish between advanced economies and emerging & developing economies, we use the classification from the World Economic Outlook (WEO), IMF. After matching the classification by WEO with the available data from TED, we end up with 128 countries in our final dataset, covering the entire period of 1995-2020, with 36 AE's and 92 EDE's.

For this study, the variables of interest from TED are – GDP at constant prices (2019 US$ PPP, in millions), capital stock – ICT and non-ICT assets (2019 US$ PPP, in millions), total persons employed (in thousands), and capital and labor composition indices (1995 = base). In the production function framework described previously in equation (5), we require natural logarithmic transformations of the aforementioned variables. The descriptive statistics of the original variables and appropriate transformations are reported in Table 1 below.

[7] The use of clustered standard errors is justified when the sample has a large N and small T, *i.e.*, the number of observations is larger than the time period under consideration. This is the case in our sample from the TED database.

Table 1: Descriptive Statistics – TED variables and log transformations

TED variables	Obs.	Mean	Std. Dev.	Min	Max
Original variables					
GDP at constant prices (Y)	3328	714556.33	1971584.9	4449.59	21427690
ICT capital stock (S^{ICT})	3276	25973.33	108929.48	0.31	2320224.4
Non-ICT capital stock (S^{nICT})	3276	2357910.4	6415599.7	6343.19	65652478
Capital quality index (Q^s)	3328	1.18	0.20	0.88	2.27
Labor quality index (Q^H)	3328	1.07	.080	0.88	1.53
Total persons employed (H)	3328	22252.1	77872.69	142.75	776215
Natural log transformations					
Log (Labor productivity) = ln $\left(\frac{Y}{H}\right)$	3328	3.41	1.14	0.17	5.43
Log (ICT capital services) = ln $(S^{ICT}Q^s)$	3276	8.01	2.39	-1.18	15.14
Log (non-ICT cap services) = ln $(S^{nICT}Q^s)$	3276	13.24	1.84	8.76	18.49
Log (Labor quality index) = ln(Q^H)	3328	0.07	0.07	-0.13	0.43
Log (Total persons employed) = ln (H)	3328	8.64	1.51	4.96	13.56

Source: Original variables are from TED and natural log transformations are based on authors' calculations.

The control variables in the regression equation are identified from the literature, and the data are obtained from various sources. The sources for these variables are outlined in Table A.2 in the Appendix. In what follows, we explain the rationale behind each control variable and the source of data used.

Control of corruption: Corruption is an institutional weakness, which adds additional costs on producers, and therefore, it is expected to hamper productivity growth. We include a measure of corruption available from World Bank World Governance Indicators in our model. This measure captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, *i.e.*, ranging from approximately -2.5 to 2.5. A country with poor governance thus receives a lower score, indicating a poor control of corruption. Given the nature of the measure, we expect a positive effect from this variable on productivity (implying a negative effect of corruption).

Share of manufacturing in GDP: The manufacturing sector is usually considered to see relatively faster changes in technology than other sectors (*e.g.*, services) of the economy.

Therefore, countries with a higher manufacturing presence are likely to see relatively faster productivity growth than others. To account for that, we include the share of manufacturing output in the economy in the model. The data is obtained from World Bank World Development Indicators, and we expect this variable to have a positive impact on labor productivity.

Internet users (% total population): The impact of investment in ICT on productivity is widely discussed in the literature (*e.g.*, Jorgenson and Vu, 2005; Jorgenson and Stiroh, 2000; Oliner and Sichel, 2002; Inklaar, O'Mahony, and Timmer, 2005; Van Ark, O'Mahony, and Timmer, 2008; Stiroh, 2005; Erumban and Das, 2016). In our data, this has been partly accounted for by the measure of capital stock and capital composition index, as the TED data on capital makes a distinction between investment in ICT and non-ICT assets. However, the impact of ICT on macroeconomic productivity can be beyond the investment effect, and the general diffusion of ICT and its accessibility to the population may affect the overall productivity. To account for this ICT diffusion effect on productivity, we use the internet penetration among the population of each country as an explanatory variable in the regression. Internet penetration is measured as the proportion of population who use internet, and the data is obtained from World Development Indicators. This variable is expected to have a positive effect.

Life expectancy at birth, total years: A healthy population and labor force are important in achieving better productivity, and longer life expectancy is a good measure of better health conditions. We include life expectancy at birth in our model, which is expected to affect productivity positively. It indicates the number of years a newborn infant would live if prevailing patterns of mortality at the time of its birth were to stay the same throughout its life. The data is based on the estimates by the United Nations, available through World Development Indicators.

***Inflation rate*:** The inflation rate is included in the model as a proxy for macroeconomic stability, which might affect aggregate productivity negatively. It is measured by the consumer price index, and is obtained from the World Development Indicators.

***Globalization Index*:** Opening national borders to the free movement of goods, services, people, and capital are considered to be important for better allocation of resources to locations where they are more efficient. Therefore, a country's openness to the world economy is likely to have important implications for productivity. Countries that are well integrated into the global economy are likely to see better productivity growth. We use the KOF Globalisation

Index, which measures the economic, social and political dimensions of globalisation, in our model. The index measures globalisation on a scale from 1 to 100.

Table 2: Summary statistics of additional control variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Control of Corruption	2688	.04	1.07	-1.72	2.47
Internet users (% population)	3018	29.77	30.78	0	99.7
Manufacturing (% GDP)	2893	14.21	6.19	.23	50.04
Life expectancy, total years	3171	70.79	9.25	35.38	85.08
KOF globalization index	3048	61.86	15.35	24.45	90.98
Inflation rate	2962	8.2	23.12	-16.12	411.76

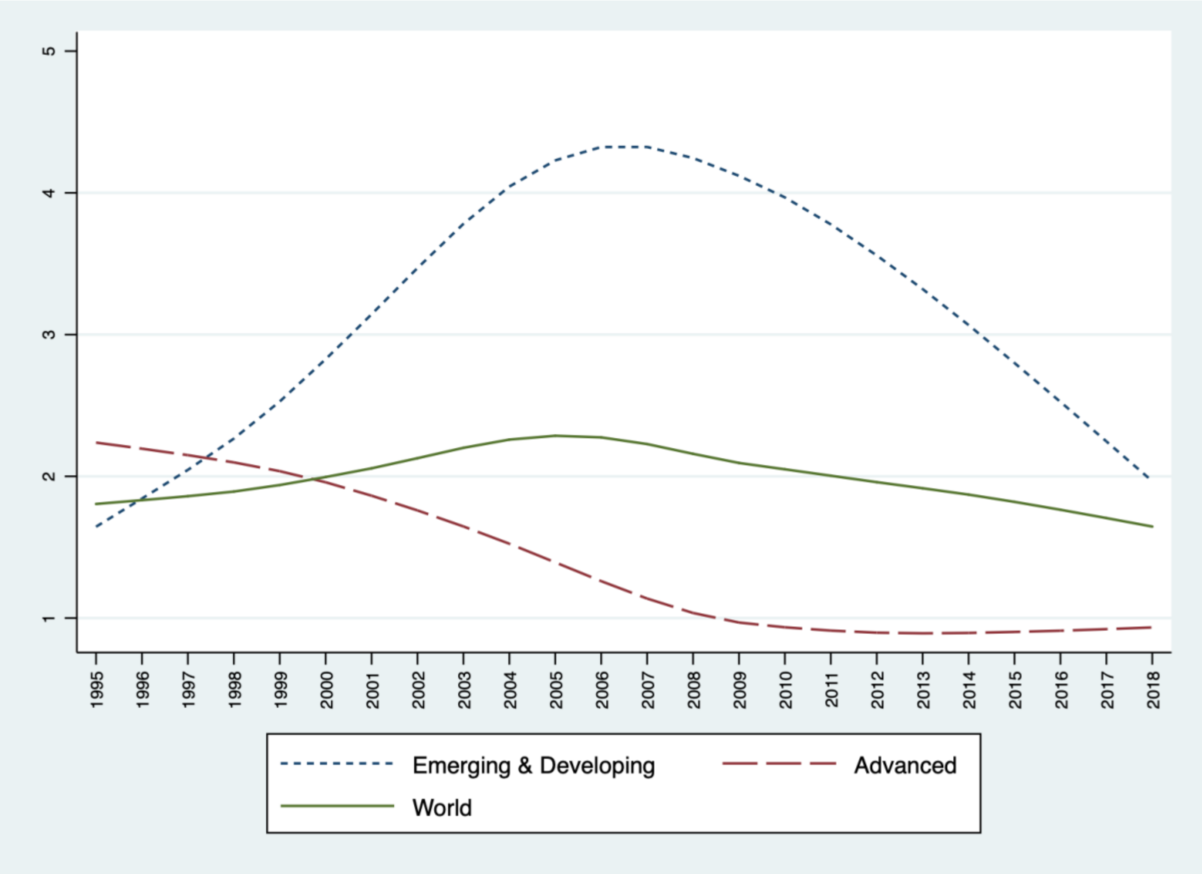
Source: Author's calculations based on the data of additional control variables.

3. Empirical Results

This section presents the empirical findings based on our descriptive and statistical analysis. We begin by discussing the trends in labor productivity growth for our broad classification, followed by an identity decomposition of labor productivity growth for TED regional aggregates. The estimation results from the CRE model and robustness checks are reported in the end.

Figure 3 traces the trend in labor productivity growth for the two groups – advanced economies and emerging and developing economies – over the period of 1995-2018. The labor productivity growth has been smoothed using the Hodrick-Prescott (HP) filter, with a parameter value of 100. It is observed that labor productivity growth of EDEs was lower than that of AEs only during 1995 till mid 1997. In all other years, global labor productivity growth was primarily driven by EDEs. Additionally, as we observed in the previous section, we can see a clear overall post-2008 slowdown in productivity for both groups. However, it is important to note that the productivity slowdown for AEs had already begun in the early 2000s much before the global financial crisis in 2008. As for the EDEs, the productivity slowdown started much later around 2009-10.

Figure 3: Trend in labor productivity growth, 1995-2018



Note: Trend growth rates are obtained using the Hodrick-Prescott (HP) filter with $\lambda = 100$
Source: Authors' illustration based on TED Regional Data, 2021.

Table 3 below provides the decomposition of labor productivity growth into GDP growth and the growth in persons employed (EMP growth) for two sub-periods – 1995-08 and 2009-18. The analysis is done for TED regional aggregates within the two broad groups (refer to Table A.1 in the Appendix). It is observed that the post-2008 global slowdown in productivity was largely a result of a slowdown in GDP growth by an average of 0.88 percentage points over the two sub-periods. This slowdown in GDP growth outweighed the fall in employment growth, thus, reducing productivity growth. The productivity growth slowdown was more drastic for the AEs as compared to EDEs, driven by the slowdown in GDP growth of 1.18 percentage points for the former as compared to 0.88 percentage point slowdown in GDP growth for the latter. Within the AEs, the 'Europe' and 'Other Advanced Economies' aggregates suffered the largest declines in GDP growth over the two sub-periods of 1.45 and 1.39 percentage points, respectively.

Within the EDE aggregate, we observe that the 'Other Developing Asia' aggregate and India saw a post-2008 productivity revival by 0.34 and 0.54 percentage points, respectively. The

‘Middle East & North Africa’ and ‘Russia, Central Asia & Southeast Europe’ aggregates saw an identical decline in GDP growth over the two sub-periods by 1.98 percentage points, while the latter saw a relatively larger decline in productivity due to its corresponding increase in employment growth of 0.2 percentage points in the second sub-period. The Chinese economy, an influential player in the emerging and developing world, saw a large post-2008 decline in GDP growth of 1.93 percentage points. This led to a corresponding fall in productivity growth of the Chinese economy by 1.34 percentage points. However, it is clear that the productivity slowdown in the EDE aggregate was substantial even if one excludes China.

Table 3: Decomposition of labor productivity growth, 1995-08 and 2009-18

	1995-2008			2009-2018		
Aggregates	GDP growth	EMP growth	Labor Productivity growth	GDP growth	EMP growth	Labor Productivity growth
World	**3.66**	**1.45**	**2.17**	**2.78**	**1.03**	**1.73**
Advanced Economies	**2.69**	**0.94**	**1.73**	**1.51**	**0.58**	**0.92**
Europe	2.50	0.93	1.55	1.05	0.39	0.65
USA	2.98	1.08	1.88	1.83	0.68	1.15
Japan	1.11	-0.06	1.17	0.67	0.24	0.42
Other Advanced Economies	4.21	1.70	2.46	2.82	1.30	1.49
Emerging Markets & Developing Economies	**4.97**	**1.57**	**3.34**	**4.09**	**1.13**	**2.92**
Latin America	3.12	2.20	0.90	1.68	1.51	0.16
Sub-Saharan Africa	4.62	2.80	1.77	4.21	2.94	1.24
Middle East & N. Africa	4.40	3.11	1.25	2.42	2.25	0.17
Russia, Central Asia & Southeast Europe	4.30	0.58	3.68	2.32	0.60	1.69
India	6.93	1.43	5.43	7.27	0.63	6.60
China	7.47	0.84	6.58	5.54	0.28	5.24
Other Developing Asia	4.59	2.23	2.31	5.13	1.66	3.42

Note: Growth rates are reported in percentage changes.
Source: Authors’ calculations based on TED Regional Data, 2021.

Table 4 provides the results from the CRE model (equation 12), presented for various model specifications. In order to make a robust inference, we utilize clustered robust standard errors along with the usual GLS-RE estimation of the model. Overall, the R-square varies in the range of 0.85 to 0.91, indicating the high explanatory power of the model in explaining the variation in labor productivity. Moreover, the between R-squared ranges from 0.86 to 0.90, indicating that, on average, 88 percent of the variation between countries in labor productivity is explained by the differences in the variables under consideration.

The first model has the basic equation with the natural log of labor productivity as a dependent variable and capital services (ICT and non-ICT) and labor (labor quantity and quality) as independent variables. It may be noted that the coefficient of labor in this specification is not similar to the elasticity of labor in the standard Cobb-Douglas specification, as the dependent variable here is labor productivity. The estimated coefficients of capital services (both the ICT and non-ICT) are positive and significant, with the elasticity of non-ICT capital services being relatively higher. The coefficient of labor, which is equivalent to the elasticity of labor minus 1, is negative as expected and is estimated at -0.8, indicating an approximate labor elasticity of 0.2. The dummy variable for the EDEs is insignificant, while the dummy for post-crisis years is negative and significant, showing a significantly lower productivity growth in the post-crisis years.

In the subsequent models, the results are presented in a hierarchical way, adding control variables one by one. The coefficients of capital services (both ICT and non-ICT) remain positive and significant in all the models, with the elasticity of ICT capital services varying between 0.03 to 0.11 - the more control variables we have in the model, the lesser is the magnitude of the coefficient. In the case of non-ICT capital services, however, the coefficient is somewhat stable, in the range of 0.27 to 0.3. Labor quality remains largely insignificant across the board, while the coefficient of employment remains mostly stable in the range of -0.74 to -0.8.

Among the control variables, the quality of governance, or the higher scores for control of corruption, has a significant positive effect, and is observed to be consistently significant across all models. The share of the internet using population, although it has a positive coefficient, is not significant. In contrast to our expectation, the share of manufacturing has shown a negative, although largely insignificant, impact on labor productivity. The variable shows a significant negative impact (albeit at the 10% significance level) in the fifth model, which is devoid of important controls such as globalization and life expectancy, which are subsequently added. In the final model, life expectancy and globalization indicators have a positive and significant impact, as expected, whereas the inflation rate, which measures the macroeconomic instability, is negative and significant.

After controlling for all these indicators, we see that the labor productivity in the emerging and developing economies is relatively higher than in the advanced economies, as exemplified previously in Figure 3. The dummy variable for the emerging and developing economies is positive and significant, and the coefficient is stable across all models that include control variables. Similarly, the post-crisis dummy variable is negative and significant, showing significantly lower productivity after the global financial crisis, for the entire sample. The interaction of the two dummy variables is meant to capture whether the impact of the crisis has been different on the emerging markets and developing economies as compared to advanced economies. The interaction term has a positive and significant coefficient in all the models. This suggests that the adverse effect of the crisis on labor productivity has been significantly intense on the advanced economies than the developing and emerging markets.

Panel A of Figure 4 below provides the partial correlation plot of a given control variable and the dependent variable, the logarithm of labor productivity, after netting out the influence of other controls. This is done through the technique of partial regression which produces an added-variable plot with a regression line of same slope as the estimates in Table 4.[8]

A confidence band is overlayed to show how the data fits the partial correlations. It is immediately clear that with the exception of inflation rate, the inference made for other independent variables does not appear to be affected by influential outliers. As for inflation rate, we observe that large observations for this variable could be influencing the estimated relationship between inflation rate and labor productivity growth in our final model, in the last column of Table 3. The high inflation rates (in the excess of 100 per cent) in the sample data are observed for countries such as Angola, Armenia, Azerbaijan, Belarus, Bulgaria, DR Congo, Georgia, Iraq, Romania, Russia, Venezuela; mostly in the late 1990's. We do not remove these high inflation data points[9] since the CRE model by construction controls for the average

[8] Note: The plots are generated using the STATA command: **xtavplot**; The methodology applies appropriate transformations to the given variables in order to net out the influence of other variables whilst explaining the variation in the dependent variable. The plots are based on the transformed variables. Refer to Gallup, J. K. (2020) for the methodology behind this command.

[9] Note that excessively high inflation rate data points had been eliminated from model. For example, Angola experienced hyperinflation (in the excess of 2000 percent) in 1995 and 1996, such data points have been eliminated.

Table 4: Regression results, Correlated Random Effects (CRE) model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln_ictK	.117***	.1074***	.1015***	.0861***	.0727***	.0506***	.0394***
	(.0229)	(.0218)	(.0215)	(.0189)	(.02)	(.0147)	(.0136)
ln_nictK	.2812***	.2988***	.2805***	.3071***	.2914***	.269***	.2863***
	(.0799)	(.0718)	(.0693)	(.0595)	(.0593)	(.0519)	(.0498)
ln_LQ	-.3074	-.1931	-.1025	.3299	.2604	.0661	-.0057
	(.2951)	(.2702)	(.258)	(.2115)	(.2052)	(.2071)	(.2469)
ln_EMP	-.8027***	-.7776***	-.7808***	-.7812***	-.7924***	-.7626***	-.7424***
	(.0735)	(.067)	(.0677)	(.0633)	(.0605)	(.0604)	(.0597)
coc_score		.1819***	.1743***	.1213***	.1131***	.0901***	.0800***
		(.0415)	(.0382)	(.0294)	(.0309)	(.0291)	(.0238)
intusr_percpop			.0006	0	.0003	0	-.0002
			(.0006)	(.0005)	(.0004)	(.0004)	(.0004)
manf_percgdp				-.0036	-.0043*	-.0034	-.0032
				(.0025)	(.0025)	(.0021)	(.0021)
lifeexp_total					.0109***	.0103***	.0118***
					(.0041)	(.0039)	(.0043)
glbindex						.0105***	.0121***
						(.0021)	(.0021)
inflrate							-.0012**
							(.0005)
d_ede	-.191	.2172*	.3031**	.3108**	.2823**	.3198***	.2994**
	(.1214)	(.1225)	(.1231)	(.1231)	(.1159)	(.1192)	(.118)
d_post2008	-.0848***	-.066***	-.0774***	-.078***	-.0876***	-.0695***	-.0637***
	(.0261)	(.0213)	(.0199)	(.0181)	(.0174)	(.0158)	(.0157)
d_interaction	.1233***	.0891***	.0981***	.1003***	.0979***	.0786***	.0687***
	(.0323)	(.0277)	(.0263)	(.0205)	(.0207)	(.0193)	(.0195)
_cons	2.0775***	1.4873***	1.3261***	1.3341***	.2056	-.2667	.1084
	(.4393)	(.4125)	(.3966)	(.4342)	(.5949)	(.6151)	(.6088)
Observations	3276	2646	2485	2303	2303	2242	2076
Overall R^2	0.8580	0.8849	0.8954	0.9010	0.9084	0.9124	0.9106
Between R^2	0.8693	0.8944	0.9032	0.8958	0.9040	0.9093	0.9092
Within R^2	0.6108	0.6264	0.6356	0.7372	0.7448	0.7625	0.7877

Note: The dependent variable is ln (Y/H). Robust standard errors obtained by clustering are in parentheses.
**** p<.01, ** p<.05, * p<.1*
Source: Author's calculations based on the TED database (2021) and data on additional controls.

inflation rates for each country (see equation (12)). Thus, the partial effect of inflation rate on labor productivity is meant to be captured by systematic differences in countries experiencing high and low inflation rates.

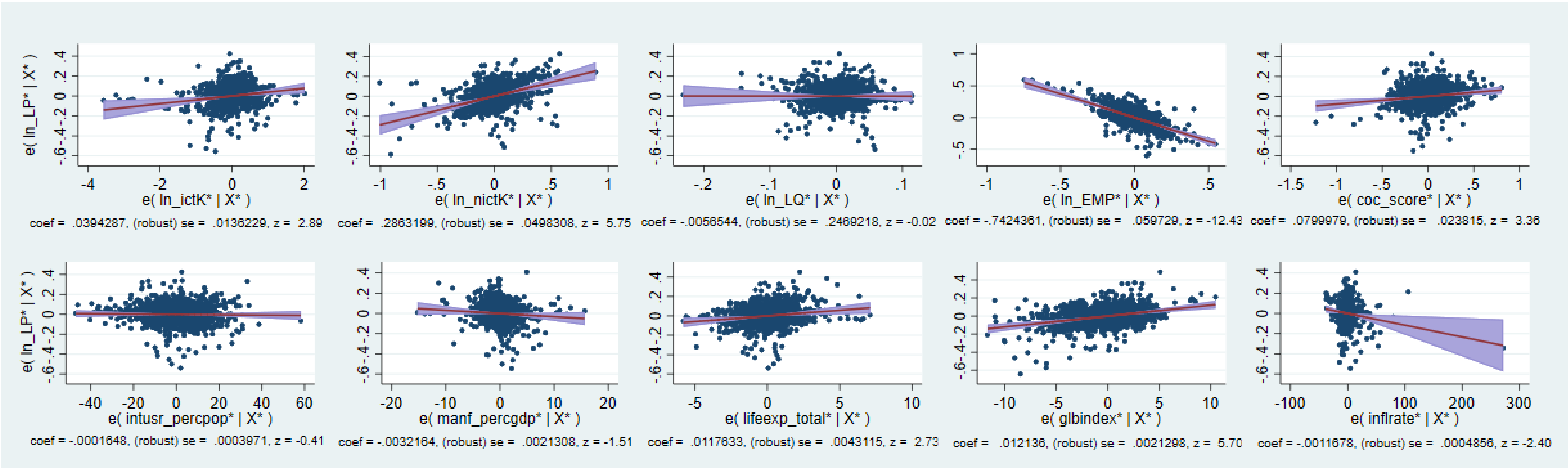
It is important to reiterate that the CRE model has a highly attractive feature of allowing correlation between the time invariant country-specific characteristics and the various explanatory variables. For example, suppose there is a landlocked country in the sample which might experience a relatively lower sea-based trade, such a characteristic can be negative related to the globalization index – via a reduced prospect of sea-based trade. Similarly, there can be various country-specific institutional structures that can be highly correlated with variables such as persons employed, inflation rate, corruption and life expectancy. Since the results of the CRE model are explicitly made robust to the existence of such practical correlations by modelling the said correlation, the observed estimates from this model are thus attractive for our analysis.

The CRE model also provides a robust regression based Hausman test by allowing the hypothesis test given in equation (14), by testing the significance of the mean values of the time-varying explanatory variables. The coefficient estimates of these mean values and their respective statistical significance levels are reported Table 4. However, the significance of these coefficients can be directly inferred from the visualization of the partial correlation plots and confidence bands for the estimated relationships between the mean values and log of labor productivity in Panel B of Figure 2. It is clear that with the exception of average ICT-based capital deepening and average persons employed, the other mean values of the explanatory variables are statistically insignificant, since the value of zero does not lie outside the confidence band for the latter variables. Thus, overall, we cannot reject RE in favor of FE as per the hypothesis test described previously in equation (12).

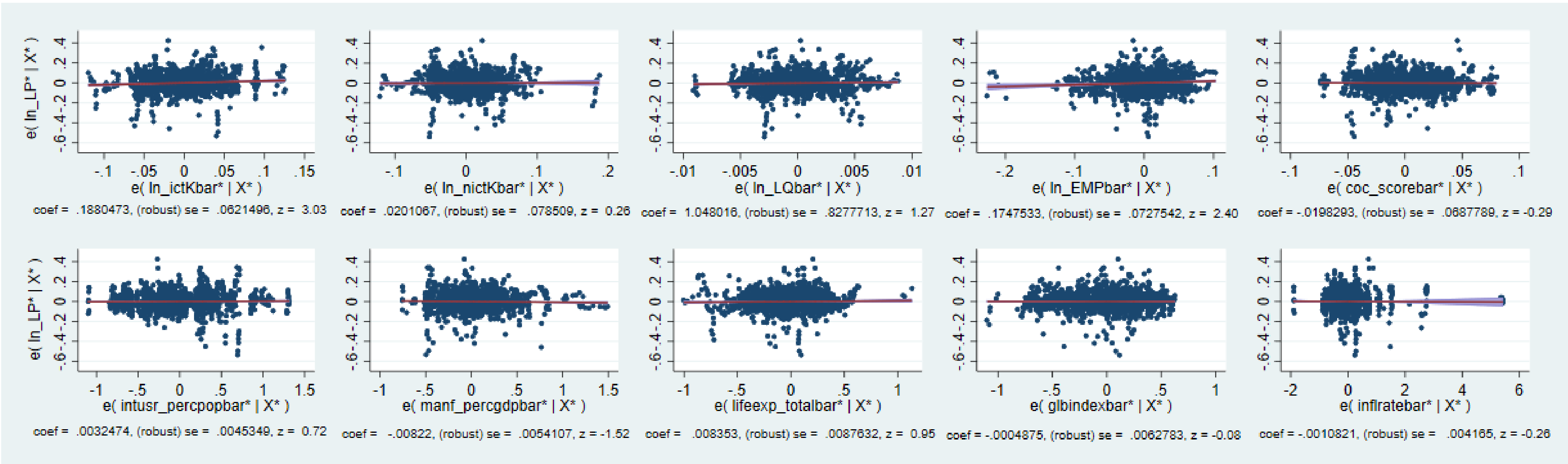
The results of the RE-GLS estimation devoid of mean values of the explanatory variables (setting $\overline{Z}_{j,i} = 0$ in equation (12)) as additional regressors, are reported in the last column of Table 4. The signs of the coefficients and statistical significance in this simple RE model are largely similar to the results of the CRE model. However, the coefficient of the dummy variable for emerging and developing economies is negative and no longer significant. It is important to note that the RE model operates on the stringent assumption of independence between the

Figure 2: CRE Model partial coefficients, time-varying explanatory variables and respective mean values

Panel A: Explanatory variables



Panel B: Mean values of explanatory variables



Source: Author's illustration based on the estimated results of the CRE model (equation 12).

Table 4: Comparison of regression results from CRE, FE and RE models

	CRE		FE	RE
	Original variables	Mean values		
ln_ictK	.0394***	.188***	.0395***	.0351***
	(.0136)	(.0621)	(.0136)	(.013)
ln_nictK	.2863***	.0201	.2862***	.3223***
	(.0498)	(.0785)	(.0496)	(.0478)
ln_LQ	-.0057	1.048	-.0041	-.025
	(.2469)	(.8278)	(.246)	(.2595)
ln_EMP	-.7424***	.1748**	-.7444***	-.6377***
	(.0597)	(.0728)	(.0595)	(.0561)
coc_score	.0800***	-.0198	.0794***	.0905***
	(.0238)	(.0688)	(.0237)	(.0263)
intusr_percpop	-.0002	.0032	-.0002	-.0004
	(.0004)	(.0045)	(.0004)	(.0004)
manf_percgdp	-.0032	-.0082	-.0033	-.0019
	(.0021)	(.0054)	(.0021)	(.0022)
lifeexp_total	.0118***	.0084	.0118***	.0095**
	(.0043)	(.0088)	(.0043)	(.004)
glbindex	.0121***	-.0005	.0122***	.0121***
	(.0021)	(.0063)	(.0021)	(.0022)
inflrate	-.0012**	-.0011	-.0012**	-.0012***
	(.0005)	(.0042)	(.0005)	(.0005)
d_ede	.2994**		-	-.12
	(.118)			(.1319)
d_post2008	-.0637***		-.0637***	-.0608***
	(.0157)		(.0156)	(.0148)
d_interaction	.0687***		.069***	.0472***
	(.0195)		(.0195)	(.0181)
_cons	.1084		4.237***	3.1102***
	(.6088)		(.4859)	(.412)
Observations	2076		2076	2076
Overall R^2	0.9106		0.6299	0.7550
Between R^2	0.9092		0.6239	0.7490
Within R^2	0.7877		0.7878	0.7797

Note: The dependent variable is ln (Y/H). Robust standard errors obtained by clustering are in parentheses. In the CRE model, mean values of the time-varying explanatory variables are estimated along with the original variables, as in equation (12).
**** p<.01, ** p<.05, * p<.1*
Source: Author's calculations based on the TED database (2021) and data on additional controls.

time invariant country-specific characteristics and the various explanatory variables. As described previously, such correlations can exist and are important to control for in the context of the relationship that we are attempting to explore, thus, the RE estimates can be biased. Since the CRE model is robust to such correlations, we prefer the CRE estimates in over the usual RE-GLS estimates. As a theoretical robustness check, Table 4 also presents the FE estimates of the time-varying explanatory variables from equation (12) by setting $\overline{Z}_{j,i} = 0$. As per equation (13), we find that the FE estimates are approximately equal to the CRE estimates (which is nothing but a RE estimation of equation (12) where $\overline{Z}_{j,i} \neq 0$). As described previously in the methodology section, the FE approach is seen as more reliable when carrying out policy analysis using aggregate data, the CRE model is able to deliver the same coefficients as one would obtain by FE estimation. Moreover, the CRE model is able to estimate the coefficient of the time-invariant group dummy, whilst also maintaining correlation between time-invariant country characteristics and the regressors.

3. Summary & Conclusions

The paper examines the impact of the global financial crisis on productivity performance of emerging markets and developing economies (EDE) as well as advanced economies (AE). The slowdown in labor productivity growth given its impact on world's lives and livelihood attracted attention of policy makers both in the different parts of the world encompassing emerging economies as well as advanced countries. There is exists significant evidence of a slowdown in advanced countries but there remains much less evidence for the set of countries defined as emerging markets including economies like China, Brazil, India to name a few on one hand and host of developing economies. The present study revisits the question of global slowdown and its consequences for labor productivity for a panel of countries comprising emerging markets, developing economies and advanced countries. The period under consideration is from 1995-2020 and using the dataset of TCB (The conference Board), the study undertakes a panel data model, in particular a correlated random effects panel regression to examine the impact of global slowdown on labor productivity. Several results warrant attention before the regression model is estimated.

First, the labor productivity growth of EDEs was lower than that of AEs only during 1995 until mid-1997. In all other years, global labor productivity growth was primarily driven by EDEs. Additionally, we can see a clear overall post-2008 slowdown in productivity for both groups. However, it is important to note that the productivity slowdown for AEs had already begun in the early 2000s much before the global financial crisis in 2008. As for the EDEs, the productivity slowdown started much later around 2009-10

Second, post-2008 global slowdown in productivity was largely a result of a slowdown in GDP growth by an average of 0.88 percentage points over the two sub-periods. This slowdown in GDP growth outweighed the fall in employment growth, thus, reducing productivity growth. The productivity growth slowdown was more drastic for the AEs as compared to EDEs, driven by the slowdown in GDP growth of 1.18 percentage points as compared to 0.88 percentage point for the latter. Within the AEs, the 'Europe' and 'Other Advanced Economies' aggregates suffered the largest declines in GDP growth over the two sub-periods of 1.45 and 1.39 percentage points, respectively.

Within the EDE aggregate, we observe that the 'Other Developing Asia' aggregate and India saw a post-2008 productivity revival by 0.34 and 0.54 percentage points, respectively. The 'Middle East & North Africa' and 'Russia, Central Asia & Southeast Europe' aggregates saw an identical decline in GDP growth over the two sub-periods by 1.98 percentage points, while the latter saw a relatively larger decline in productivity due to its corresponding increase in employment growth of 0.2 percentage points in the second sub-period. The Chinese economy, an influential player in the emerging and developing world, saw a large post-2008 decline in GDP growth of 1.93 percentage points. This led to a corresponding fall in productivity growth of the Chinese economy by 1.34 percentage points. However, it is clear that the productivity slowdown in the EDE aggregate was substantial even if one excludes China.

In the context of the present analysis, practical correlations between the time invariant country characteristics and explanatory variables can occur – the RE model is biased due to its strong assumption of exogeneity of explanatory variables with such characteristics. Additionally, the FE approach is unable to estimate the group dummy variable for EDEs due the process of time demeaning of variables. Given these theoretical limitations of the RE and FE models, we utilize a correlated random effects model (CRE) which allows much more flexibility. In particular, The CRE model allows us to maintain correlation between the explanatory variables and the time-invariant country characteristics whist also allowing the estimation of a time invariant group dummy variable for emerging markets and developing economies. This approach simultaneously controls for the average values of the time-varying variables, thus, allowing the partial effect of systematically high/low values of the explanatory variables to impact the dependent variable. Several interesting results emerge from the estimation of the CRE model.

First, we observe that the coefficients of capital services (both ICT and non-ICT) remain positive and significant in all the models, with the elasticity of ICT capital services varying between 0.03 to 0.11 - the more control variables we have in the model, the lesser is the magnitude of the coefficient. In the case of non-ICT capital services, however, the coefficient is somewhat stable, in the range of 0.27 to 0.3. Labor quality remains largely insignificant across the board, while the coefficient of employment remains mostly stable and significant in the range of -0.74 to -0.8.

Second, amongst the control variables, the quality of governance/or the higher scores for control of corruption, has a significant positive effect, and is observed to be consistently significant across all models. Life expectancy and globalization indicators have a positive and significant impact, as expected, whereas the inflation rate, which measures the macroeconomic instability, is negative and significant.

Finally, our main assertion remains that since we observe that the predicted labor productivity in the emerging and developing economies is relatively higher than in the advanced economies since the dummy variable for the emerging and developing economies is positive and significant. The post-crisis dummy variable is negative and significant, showing significantly lower productivity after the global financial crisis, for the entire sample. The interaction of the two dummy variables is also included, which is meant to capture whether the impact of the crisis has been different on the emerging markets and developing economies as compared to advanced economies. The interaction term has a positive and significant coefficient. This suggests that the adverse effect of the crisis on labor productivity has been significantly intense on the advanced economies than the developing and emerging markets. We conclude by arguing that the impact of global crisis on declining productivity is less for emerging markets and developing economies in contrast to advanced economies where the impact of the crisis on productivity decline is stronger.

Bibliography

Baily, M. N. and Montalbano, N. (2016). Why is U.S. Productivity Growth So Slow? Possible Explanations and Policy Responses. *Hutchins Center Working Paper*, no. 22.

Bartelsman, E. J. (2000). Understanding Productivity: Lessons from Longitudinal Microdata. *Journal of Economic Literature, 38*(2), 569-594.

Brynjolfsson, E. and McAfee, A. (2011). Race against the Machine – How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy, Digital Frontier Press: Massachusetts.

Byrne, D., Fernald, J. & Reinsdorf, M. (2016). Does the United States Have a Productivity Slowdown or a Measurement Problem?. *Brookings Papers on Economic Activity* (017), 1-74.

Corrado, C., Hulten, C. & Sichel, D. (2009). Intangible Capital and U.S. Economic Growth. *Review of Income and Wealth*, Series 55, no. 3.

Crafts, N. (2018). The productivity slowdown: is it the 'new normal'?. *Oxford Review of Economic Policy*, *34*(3), 443-460.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2017). Declining dynamism, allocative efficiency, and the productivity slowdown. *American Economic Review*, *107*(5), 322-26.

Dieppe, A. (2020). Global Productivity: Trends, Drivers, and Policies. *World Bank Publications*, World Bank, no. 34015, December.

Eichengreen, B. (2015). Secural Stagnation: The Long View. *NBER Working Paper Series*, no. 20836.

Erumban, A. A. and van Ark, B. (2018). Productivity in the Global Economy. Chapter 2, In Das, D. K. (Ed.): *Productivity Dynamics in Emerging and Industrialised Countries*, Routledge India.

Gallup, J. K. (2020). Added-variable plots for panel-data estimation. *The Stata Journal*. 2020, 20(1), 30-50.

Goodridge, P., Haskel, J. and Wallis, G. (2016). Accounting for the UK Productivity Puzzle: A Decomposition and Predictions. *Economica, 85*.

Goldin, I., Koutroumpis, P., Lanford, F. and Winkler, J. (2021). Why is Productivity slowing down?. *Oxford Martin Working Paper Serieson Economic and Technical Change*, no. 2021-6.

Gordan, J. R. (2016). The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War. Princeton University Press.

Gordan, J. R. and Sayed, H. (2019). The Industry Anatomy of the Transatlantic Productivity Growth Slowdown. *NBER Working Paper Series*, no. 25703.

Gordon, R. J. (2016). The Rise and Fall of American Growth, Princeton, NJ: Princeton University Press.

Gregorio, J. D. (2018). Productivity in Emerging Market Economies: Slowdown or Stagnation?, Working Paper 18-12, *Peterson Institute for International Economics*.

Inklaar, R., O'Mahony, M. and Timmer, M. P. (2005). ICT and Europe's Productivity Performance: Industry-level Growth Account Comparisons with the United States. *Review of Income and Wealth*, *51*(4), 505-536.

Jorgenson, D. W. and Stiroh, K. J. (2000). U.S. Economic Growth at the Industry Level. *American Economic Review*, *90*(2), 161-167.

Jorgenson, D., & Vu, K. (2005). Information Technology and the World Economy. *The Scandinavian Journal of Economics*, *107*(4), 631-650.

Oliner, S. D. and Sichel, D. (2002). Information Technology and Productivity: Where Are We Now and Where Are We Going?. *Journal of Policy Modeling*, *25*(Q3), 15-44.

Ramskloger, P. (2015). Tracing the Origins of the Financial Crisis. OECD Journal: Financial Market Trends, *14*(2), OECD 2015.

Reinhart, C. M. and Rogoff, K. S. (2014). Recovery from Financial Crises: Evidence from 100 Episodes. *American Economic Review*, Papers & Proceedings, *104*(5), 50-55.

Summers, L. H. (2014). US Economic Perspectives: Secular Stagnation, Hysteresis, and the Zero lower Bound. *Business Economics*, *49*(2), 65-73.

Syverson, C. (2011). What Determines Productivity?. *Journal of Economic Literature*, *49*(2), 326-365.

Syverson, C. (2017). Challenges to Mismeasurement Explanations for the US Productivity Slowdown. *Journal of Economic Perspectives*, *31*(2), 165-186.

The Conference Board (2021), The Conference Board Total Economy Database.

Timmer, M. P., Erumban, A. A., Los, B., Stehrer, R. and de Vries, G. J. (2014). Slicing Up Global Value Chains, Journal of Economic Perspectives, *28*(2), 99-118.

Timmer, M. P., Los, B., Stehrer, R. and de Vries, G. J. (2016). An Anatomy of the Global Trade Slowdown based on the WIOD 2016 Release. *GGDC Working Paper*, no. 162.

van Ark, B. and Jaeger, K. (2017). Recent Trends in Europe's Output and Productivity Growth Performance at the Sector Level, 2002-2015. International Productivity Monitor, 2017, *33*, 8-23.

van Ark, B., Erumban, A. A. and de Vries, K. (2021). How to not Miss a Productivity Revival Once Again. *National Institute Economic Review*, *225*, 9-24.

van Ark, B., Erumban, A. A., Corrado, C. and Levanon, G. (2016). Navigating the Digital Economy: Driving Digital Growth and Productivity from Installation to Deployment. The Conference Board.

van Ark, B., O'Mahony, M., Timmer, M. P. (2008). The Productivity Gap between Europe and the United States: Trends and Causes. *Journal of Economic Perspectives*, *22*(1), 25-44.

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data. Cambridge: MIT Press.

WEO Groups and Aggregates Information, World Economic Outlook (2021).

Wu, H. X., Krishna, K. L., Das, D. K., & Das, P. C. (2017). How Does the Productivity and Economic Growth Performance of China and India Compare in the Post-Reform Era, 1981-2011?. *International Productivity Monitor*, *33*, 91-113.

Appendix

Table A.1: Country classification – TED and WEO matched

Country Group	Country names
Advanced Economies	
Europe	All current 27 members of the European Union as well as the United Kingdom, Iceland, Norway and Switzerland.
Other Advanced Economies	Australia, Canada, Hong Kong, Israel, New Zealand, Singapore, South Korea, Taiwan.
Others	USA and Japan
Emerging & Developing Economies	
Latin America	Argentina, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Jamaica, Mexico, Paraguay, Peru, Uruguay, Venezuela.
Sub-Saharan Africa	Angola, Botswana, Burkina Faso, Cameroon, Chad, Congo (Republic), Cote d'Ivoire, DR Congo, Ethiopia, Gabon, Ghana, Kenya, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, Zambia, Zimbabwe.
Middle East & North Africa	Algeria, Bahrain, Egypt, Iran, Iraq, Jordan, Kuwait, Lebanon, Morocco, Oman, Qatar, Saudi Arabia, Sudan, Syria, Tunisia, United Arab Emirates, Yemen.
Russia, Central Asia & Southeast Europe	Albania, Armenia, Azerbaijan, Belarus, Bosnia Herzegovina, Georgia, Kazakhstan, Kyrgyz Republic, Macedonia, Moldova, Russian Federation, Serbia, Tajikistan, Turkey, Turkmenistan, Ukraine, Uzbekistan.
Other Developing Asia	Bangladesh, Cambodia, Indonesia, Malaysia, Myanmar, Pakistan, Philippines, Sri Lanka, Thailand, Vietnam.
Others	India and China

Source: Authors' compilation based on the matching of TED regional aggregates and WEO classification.

Table A.2: Data sources

Additional control variables	Data source
Control of corruption (estimate)	Extracted from World Governance Indicators, World Bank
Internet users as a percentage of total population	Extracted from WDI and sourced from International Telecommunication Union (ITU) World Telecommunication/ ICT Indicators Database.
Manufacturing, value added (% GDP)	Extracted from WDI and sourced from World Bank national accounts data, and OECD National Accounts data files.
Services, value added (% GDP)	Extracted from WDI and sourced from World Bank national accounts data, and OECD National Accounts data files.
Life expectancy at birth, total years	Extracted from WDI and sourced from: 1. United Nations Population Division: World Population Prospects (rev. 2019) 2. Eurostat: Demographic Statistics 3. United Nations Statistical Division: Population & Vital Statistics Report (various years) 4. U.S. Census Bureau: International Database 5. Secretariat of Pacific Community: Statistics & Demographic Programme.
Inflation rate, consumer prices (annual %)	Extracted from WDI and sourced from International Monetary Fund, International Financial Statistics data files.
Globalization Index	Extracted from KOF Globalization Index, KOF Swiss Economic Institute.

Source: Authors' compilation based on the sources for the additional controls.